Essays on Immigration, Human Capital and Technical Change

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The Faculty of Economics, Business Administration and Information Technology of the University of Zurich hereby authorizes the printing of this dissertation, without indicating an opinion of the views expressed in the work.

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Chairman of the Doctoral Board: Prof. Dr. Josef Zweimüller

Preface

"*Don't be trapped by dogma, which is living with the results of other people's thinking. Don't let the noise of others' opinions drown out your own inner voice. And most important, have the courage to follow your heart and intuition. They somehow already know what you truly want to become. Everything else is secondary.*" Steve Jobs (2005), Stanford CA.

For me, pursuing PhD studies in economics was an adventure and a formidable journey. It all started out by graduating from economic geography, a branch of social science where - at least at the University of Zurich - qualitative methods dominated the process of knowledge creation and where social science and natural and information science would easily blend and create new ideas. Despite all my passion for economics, my first years as a graduate student were characterised by a process of finding out how creativity and ideas from other fields can be integrated into the seemingly formal and dogmatic world of economics. It is thanks to great role models, most importantly Fabrizio Zilibotti and Ernst Fehr, that I am now confident that any good idea can make it in the realm of economics as long as it is carefully done. I am very grateful for this insight!

First, I would like to express my deep gratitude to my thesis advisors Fabrizio Zilibotti and David Dorn, and also to Josef Zweimüller and Rainer Winkelmann. Fabrizio Zilibotti introduced me to the fascinating world of economic growth while I was still a Master student. During the many years he supervised me as a diploma thesis writer and as a PhD student, he taught me a wealth of skills and unwaveringly insisted on and demonstrated the value of carefully crafted research. I am also particularly grateful for his immediate support for my intention to visit the LSE and the UC Davis. David Dorn's own work contributed greatly to inspiring my own first paper in labor economics and, at a later stage, our numerous discussions helped developing and sharpening my ideas. Josef Zweimüller helped broadening my empirical toolkit while co-authoring the third paper in this thesis. Together with Rainer Winkelmann, he provided an 'open home' and learning environment for me as an aspiring applied researcher.

Throughout my journey, I have been lucky to be accompanied and supported by many outstanding people and friends. Dominik Rohner, Christian Hepenstrick, Jean-Philippe Wüllrich and Andreas Kuhn were important role models from the beginning. Claudia

Bernasconi deserves credit for talking me into pursuing PhD studies in the first place. She and Bea Kraus have been very encouraging throughout my years as PhD student and joined in for countless coffee breaks with funny and energising conversations when the morale deserved a lift. Ronald Indergand, Peter Rosenkranz and Arnd Klein accompanied me through grad school and became good friends and members of an eclectic group sifting through the economic classics. Particular thanks go to Roni, who co-authored the second paper of this thesis and has been a dream sparring partner. I am also very grateful for the very collaborative and friendly working environment I found at the Chair of Macroeconomics and Political Economy with Arber Fazlija, Andreas Müller, Christoph Winter, Stephanie Raimander, Sebastian Ottinger and Matthias Schief. Unforgotten are also the illuminating and entertaining breaks with my fellow PhD students and friends Simon Alder, Lea Cassar, Sandro Favre, Johannes Kunz, Philippe Ruh, Michael Siegenthaler, Andreas Steinhauer and Franziska Weiss.

Visiting the LSE and UC Davis proved to be of integral importance to grow, learn new skills and 'find my own pond' by being exposed to a larger crowd of applied economists. I benefited greatly from comments and discussions with Massimo Anelli, Colin Cameron, Georg Graetz, Felix König, Alan Manning, Guy Michaels, Gianmarco Ottaviano, Barbara Petrongolo, Jörn-Steffen Pischke, Marta De Philippis, Dave Rapson, Kevin Shih and John Van Reenen. Giovanni Peri has been an incredibly welcoming host at the UC Davis with an infectious optimism and belief that everything is possible. He was working closely with me and co-authored the first paper of this thesis. I benefited tremendously from his knowledge, advice and positive example, and I am very grateful for this.

Finally, I would like to thank my friends Jürg, Stephan, Vera, Stefan, Claudio, Damian, Annette, Constanza, Susanne and Enrico, who all were encouraging and supportive in many different ways. In particular, I would like to thank Fanny for all the nice distractions and the wonderful moments that made this journey so joyful. I am also deeply grateful to my uncles, Rolf and Beat, who passed on the fascination for deep knowledge at a very early stage, and to my family, Doris, Max and Tina, for always believing in me and unconditionally supporting me at all times.

Andreas Beerli, Zurich, October 2015

Contents

1 Introduction

This thesis consists of three essays on applied aspects of labour economics and economic growth. One of the key challenges of doing applied work is to strike a balance between interesting and important questions and rigorous empirical analysis. A rigorous empirical analysis requires a "clean identification strategy" in the sense that the illustrated relationship between two variables has a causal interpretation. At least since Angrist and Pischke (2010) heralded the "*credibility revolution in empirical economics*", the most credible empirical identification strategies (or 'designs') use variation in the data, which is as good as randomly assigned. The key idea is to compare the outcomes of otherwise similar individuals or groups, which have been randomly assigned into treatment and control group, orientating on the idea of an experiment. Advocates of this idea claim that adhering to this standard will not only transform applied economic research but also improve policy advice: "*Creating a culture in which rigorous randomised evaluations are promoted, encouraged and financed has the potential to revolutionise social policy during the 21st century, just as randomised trials revolutionised medicine during the 20th.*" Duflo et al. (2004)

The credibility revolution of empirical designs comes at a cost. On the one hand, finding good, read exogenous, variation considerably limits the set of interesting and important questions to which an applied researcher has the hope of finding plausibly exogenous variation. On the other hand, some pundits argue that there is too much focus on exploiting exogenous variation to answer rather unimportant questions or to just inform policy makers that 'policy A causes behaviour B' rather than *why* 'policy A causes behaviour B'. Along these lines Deaton (2009), for instance, argues that researchers should focus more on using credible estimation techniques to illustrate and analyse predictions of individual behaviour from economic theory. This might help improving the external validity of empirical findings.

This discourse influences, which type of research is considered as most credible, especially by young researchers, and I tried to consider both sides in all essays of my dissertation: From a methodological perspective, all essays follow the idea of combining theory-guided analysis with rigorous causal estimation techniques. This means that they start out from a (often practical) question, use parts of different economic theories to organise thoughts and form expectations about the behaviour of individuals or groups thereof and test these implications using data and carefully adapted empirical ‘designs’.

For chapter two and chapter three of this thesis, policy issues have been an key source of inspiration. One such issue is immigration. While economists usually consider migration as beneficial in the aggregate, a heated debate about ‘winners’ and ‘losers’ held centre stage in the arenas of politics, economics and the media. In Switzerland, this debate has gained momentum through the enactment of the Agreement of Free Movement of Persons in 2002 which opened the Swiss borders for workers from the European Union and lead to an unprecedented inflow of migrant workers.

In *chapter two*, which is joint work with Giovanni Peri, we analyse the effect of opening the Swiss border on the inflow of immigrants and the consequences for natives in the labour market. From the perspective of an applied researcher, the integration of Switzerland into the European labour market accidentally created a close to perfect environment to study these questions. In particular, two different parts of the country, the border region and the non-border region have experienced different timing in the implementation of the free movement policy. This created a time window from 2004 to 2007, in which the border region was essentially open to immigrants from EU, while non-border region was not.

We leverage this differential degree of openness of the border region compared to the non-border region, to analyse the effect of opening the border on the inflow of immigrants in a difference-in-difference design. This shows that opening the border increased the share of new immigrants in the border region by 3 to 4 percentage points of total employment relative to the non-border region. Most of the differential increase in new immigrant employment took place during the time window in which both regions were maximally different in terms of openness to immigration.

When we analyse the consequences for native groups of workers, we find no evidence for negative effects of opening the border on average wages or hours worked of natives consistent with the common economic believe that immigration does usually not harm existing groups. Yet, the effect on the aggregate disguises that different subgroups of the population seem to have experienced quite heterogeneous effects. In particular, we find a positive effect of opening the border and the consequential inflow of immigrants on the wages of highly educated native workers and a negative effect on total hours worked of natives and earlier immigrants with a middle education while low educated workers seem unaffected. This result seem puzzling at first sight, as the bulk of the increase in immigrant exposure was in the group of highly educated workers and conventional economic theory would predict that similar workers suffer the most from increased labour market competition. We do find, however, some evidence for more recent extensions of this theory stating that natives might move into job profiles where they are more complementary to newly arriving immigrants which explains why their wages benefit from immigration.

The research question of *chapter three*, joint with Ronald Indergand, was inspired by the observation that newly arriving immigrants in Switzerland became increasingly highly educated. In particular, between 1990 and 2010 the share of newly arriving immigrants with a tertiary educated almost tripled from 17% to 47%. This naturally raises the question about the factors driving this phenomenon. A combination of the literature on the selection and geographical sorting of immigrants and new advances in the literature of skill-biased technical change predict that the share of highly educated immigrants increases the most in local labour market which experience larger technology-driven shifts to the demand for skill. We use a measure of local, technology-driven demand-shifts inspired from the recent literature on job polarisation (in particular Autor and Dorn (2013)), to identify the influence of demand-pull forces and separate them from the influence of changes in educational attainment in origin countries (a supply-push factor) and changes in immigration restrictions. Our analysis provides three main insights.

First, the skills, which immigrants bring to destinations, are strongly demand-driven. In particular, the same long-run trends, which affected the labour market of native workers, also influence the skills of immigrants: The introduction of automation technologies such as computers or industrial robots since the 1980s replaced millions of typical middle class jobs in clerical occupations or blue-collar workers in manufacturing. At the same time, it boosted the demand for highly skilled professionals such as managers, engineers or creative workers who were able to use these new machines effectively. In turn, this skill-bias in recent demand trends affected the educational structure of migration flows. While migrants almost exclusively worked in elementary occupations prior to the 1980s, the "new immigrants" show much stronger attachment to high-skilled jobs.

Second, the contribution of educational supply in the origin countries to the skill-mix of immigrants in destinations seems to be more nuanced. The rising education levels in the origin countries would predict that the largest gain would accrue among the group of new immigrant with a middle education a far more balanced educational distribution compared to the actual distribution among new immigrants which is more skewed in favour of highly educated workers. Since most gains in educational attainment accrued below college level, this would suggest that immigrants should have experienced the strongest gains in middle education levels. Yet, far stronger gains occurred at the top in the group of tertiary educated workers with very modest gains below. This highlights the important role of demand trends.

Third, we show that immigration policy can qualify, to some degree, the effects of the first two long-run drivers. The effect of policy changes depends on the interaction between the self-selection of immigrants and the way immigration restrictions affect the incentives of workers with different skills to immigrate.

In *chapter four*, which is joint work with Franziska Weiss, Fabrizio Zilibotti and Josef Zweimüller, we analyse a cause rather than the consequences of technical change. Here the research question is inspired by recent developments in the theory of economic growth. The key idea is based on an observation by Engel (1857), who found that households change the relative composition of their consumption bundle as they move into higher income groups. Rather than consuming more of all items in their existing consumption bundle, richer households reallocate relatively less expenditure to necessity goods and more to luxury goods, thus creating new markets for new consumer goods. Recent theories of growth with directed technical change, which incorporated this fact, predict that the development process is characterised by demand-driven waves of technical progress: The expectation of a future expansion in market size for the product of a particular industry initiates a boom in innovation activities in that industry.

To investigate the link between market size expansion and technical change, we make use of China's growth miracle, which propelled half a billion people out of poverty and created a new middle class of consumers with discretionary income to spend on consumer goods. We measure market size in sixteen different durable good industries using household survey data on the ownership of consumer durables which we link to information on innovation activities of manufacturing firms in the same industries.

One potential problem with actual, observed market size is that it could be the consequence rather than the cause of innovation activities. This would be the case, if innovation activities affect the quality or price of products, which *endogenously* increases their market size. In this case, ownership of a product would increase even without a change in the income distribution, simply because consumers in given income group find a product more desirable. To account for this problem, we construct a potential market size measure that is based on stable ownership rates for income groups and only exploits the variation in the income distribution over time. This potential market size measure serves as an instrumental variable with which we *identify* the effect of market size on the innovation activity of firms. The results show that, indeed, market size affects firm-specific total factor productivity, our favoured measure for innovation activity. Furthermore, we find that this effect is much stronger for non-exporting firms.

2 The Labor Market Effects of Opening the Border New Evidence from Switzerland[1]

Joint with Giovanni Peri

2.1 Introduction

Several pundits argue that loosening immigration restrictions or, even more, opening borders to labor mobility from abroad will syphon-off jobs to immigrants and worsen native labor market perspectives.[2] Employers, however, usually welcome access to foreign workers, which allows them a broader, more diverse labor force and some of them claim that more labor market openness would produce expansion and productivity growth with positive effects on native workers as well as firms.[3] The academic literature has produced many studies on the effects of immigrants on labor market outcomes of native workers, mostly finding small wage effects.[4] None of the studies we are aware of, however, identifies the effects using differences in *immigration policies* across otherwise similar labor markets. The traditional literature in this field exploits other sources of variations to address this question. The most popular is to leverage the differential historical presence of immigrants across areas (labor markets) due to their different past settlements to construct different inflows of immigrants and track their labor market impact on natives (e.g. Card (2001), Peri and Sparber (2009), Dustmann et al. (2013)). Alternatively, different emigration-push episodes from sending countries such as the collapse of the Soviet Union (Friedberg (2001), Borjas and Doran (2015)), the return of French expatriates from Algeria (Hunt, 1992), the return of ethnic Germans from Romania and Bulgaria (Glitz, 2012) are used

[1]An updated version of this chapter became available in the working paper series of the National Bureau of Economic Research (Working Paper No. 21319), see Beerli and Peri (2015).

[2]See for instance "For Every New Job two new Immigrants" by Camarota and Zeigler (2015), February 2015 available at http://cis.org/for-every-new-job-two-new-immigrants.

[3]See for instance "Hire the best workers wherever they are" by Vadhwa (2013), Wall Street Journal, Sept. 3rd, 2013, available here: http://wadhwa.com/2013/09/03/washington-post-hire-the-best-workers-wherever-they-are.

[4]See Lewis and Peri (2014) for a review of the literature.

in the hope of capturing an exogenous shift in the supply of immigrant workers. Those studies, however, by using sending country shocks do not shed light on the plausible effects of a change in labor immigration policies which would first affect the number of immigrants (but we do not know how much and how fast) and, in turn, labor market outcomes. If we are mostly interested in the economic impact of immigration policies we should design research that can assess the impact of such policies directly.

In this paper we estimate the effect of opening the border on immigration and labor market outcomes by exploiting policy changes in Switzerland which had different timing in different regions. The Swiss reforms implemented between 1999 and 2007, had different timing in two type of regions: The Border Region (BR) which are Swiss regions sharing a national border with a foreign country and the non-border region (NBR) which are inside Switzerland. Hence, we can use the differential liberalization of immigration policies between these two types of regions to infer, using a difference-in-difference approach, first the impact of policies on immigration and, second, the impact on the native labor market outcomes. The two types of regions (border and non-border) include many different municipalities, which we will use as units for our analysis. Municipalities may be subject to differential economic forces, and we need to control for labor demand proxies. Unobserved shocks to labor demand and economic conditions can threaten the identification, if correlated with the differential implementation of the reforms. One advantage of our empirical design is that it allows us to test whether migration and economic variables had a pre-1999 trend differential between BR and NBR municipalities that simply continued in the policy period or if the differential policy period generated economic and migration differences between the regions.

An appealing feature of the Swiss case is that we can identify a clear pre-policy period (before 1999) when Switzerland, having refused the European Common Market Policies did not have a policy of free labor mobility for European citizens. In these years before 1999 there were no relevant changes in immigration policies. In 1999, Switzerland signed the agreement of free movement of persons with the EU. This agreement, however, to become operational needed to go through ratification and implementation stages and those were slow and uncertain. One group of foreign individuals was most likely to be the first in line to be affected by these agreements. These were the cross-border workers (CBW henceforth) who worked in Switzerland but resided in a neighbouring EU country (Austria, France, Germany or Italy). The CBW had existed in Switzerland for a long time and they were only allowed to work in the border region. Their number and permits were subject to restrictions before 1999 and administered at the Cantonal level. After 1999, however, this group experienced gradually easier entry and in 2004, fully executing the free mobility agreement, they were granted full and free access to the labor markets of the border region. The non-border region, instead, could not host this type of immigrant workers. The other working immigrants were called Resident Immigrants (RI henceforth) and were in most respects identical to CBW, except that they resided in Switzerland and could work in both the BR and the NBR. The restrictions on the number of these immigrants were maintained (although relaxed) during the whole 1999-2007 period by quotas set at the Federal level. In 2007, free mobility of all European workers (CBW and RI) was granted in both regions (BR and NBR) and hence the policy difference between them ended.[5] The described sequencing of events implies that between 1999 and 2007 the BR experienced a progressive liberalization of immigration for part of their immigrants workers (the CBW) while the NBR that could only employ RI did not.

To exploit the differences described above we consider the sum of RI and CBW as the relevant group of new foreign-born workers in Switzerland. Let us emphasize that RI and CBW were very similar types of immigrants, from a labor point of view. They largely originate from the same countries (mainly Germany, France and Italy), they are similarly educated and work in similar occupations. Hence, it makes sense to combine the two types into one aggregate group of new foreign-born labor. We use the pre-1999 differences in their share of total employment (in municipalities that are in the BR and the NBR) and the evolution of these shares in the first (1999-2004) and second Phase (2004-2007) of the reforms to capture the impact of those reforms on the inflow and labor supply of immigrants. Within this framework the progressive labor market liberalization for CBW between 1999 and 2004 and their fully free mobility after 2004 in the BR affected the potential immigrant supply in the BR but not in the NBR. Hence we can adopt a simple difference-in-difference design exploiting the differential policies in the two regions. In 2007, municipalities in both regions adopted full mobility of all workers from seventeen countries of the European Union. We distinguish three Phases in our baseline analysis. The period 1994-1999 is the *pre-policy Phase* during which RI and CBW both faced immigration restrictions. Then *Phase 1*, takes place between 1999 and 2004. During this period the restrictions on CBWs were progressively reduced so that the BR experienced somewhat larger openness relative to the NBR. Finally in *Phase 2*, from 2004 to 2007 mobility is fully liberalized for CBW in BR, and hence this region enjoy the highest openness relative to NBR. Although the policy difference between regions were eliminated in 2007, inertia in migration flows may imply some delays in the relative adjustment of the NBR, a point which we will illustrate further. This is why we consider the post-2007 as an extension of Phase 2.

The difference-in-difference analysis of new immigrants reveals that the enactment of

[5] The freedom of mobility was first extended to citizens of Western European countries in 2007. Only in 2011 citizen of Eastern European countries that were members of the European Union were allowed the same access. See section 2.3 for more details about the reform.

the policies granting free mobility to CBW increased the share of new immigrants in the BR by 3-4 percentage points of total employment after 1999, with most of the growth taking place in the 2004-2007 period when free mobility of cross-border immigrants was implemented. While the effect is significant, it is far from being a flooding with immigrant workers, which is often considered the possible result of open borders in view of prevailing cross-country income differences.[6] The effect is quite small and it takes some time to take place. Importantly we can also check that before 1999, there is not much of a differential trend in the relative inflow of new immigrants in the BR and the NBR. This suggests an important role of the policy in increasing the inflow of new immigrants, which became especially pronounced after 2004. This differential inflow between the BR and the NBR remains significant even after controlling for a very demanding set of municipality fixed effects and proxies for industry-driven, local labor demand.

Newly arriving immigrants during this period were mainly highly educated. Consequently, one can expect strongest competition with highly and middle educated native workers, while less educated natives may benefit from some complementarity. Hence we analyze the impact of opening the border on average wages and employment of Swiss workers, and on educational sub-groups (tertiary educated, secondary educated and primary educated). Our findings show that the average wage of natives and earlier immigrant workers were not significantly affected by the opening policy and the induced inflow of immigrants. In addition, we do not find evidence of displacement of average native workers but some hints that employment of earlier immigrants might have suffered to a small extent. The zero effect in the aggregate combine small wages gains for highly educated natives and some employment losses of middle educated natives and earlier immigrants.

An analysis of changes in the management structure among education group reveals that the increase in immigrant exposure induced highly educated natives to climb up in the management hierarchy leading to a higher share of workers in the highest management positions among highly educated workers. These findings help explaining, why highly educated natives might have gained from the inflow of similarly educated new immigrants. In the other side, we also find that immigration had an effect on the task content of jobs in which middle educated workers are employed. Immigration had a negative effect on the share of middle educated workers employed in jobs requiring 'professional know-how' and 'qualified work input' and a positive effect on these share of middle educated workers employed in 'simple and repetitive job tasks'. Our estimates do not reveal that a similar reshuffling across management positions and job tasks took place among earlier

[6] The ratio of real GDP per capita (PPP adjusted) between origin countries and Switzerland was 80% for Italy, 82% for France, 86% for Germany and 94% for Austria in 2000 (Heston et al., 2011). While not as large as income differences between Eastern and Western European countries, the considered countries have high proximity and low cost of migration to Switzerland.

immigrants.

The rest of the paper is organized as follows. Section 2.2 reviews the literature, Section 2.3 describes the Swiss policies and section 2.4 describes the data and the variables. Section 2.5 presents and discusses the empirical specification, the identification and shows the main estimates of the effect of policies on immigration. Section 2.6 analyzes the effects on native labor market outcomes in the aggregate. Section 2.7 presents results for subgroups of natives and earlier immigrants. Section 2.8 concludes the paper.

2.2 Literature Review

As mentioned above the literature on the labor market effects of immigrants is vast and we refer the reader to recent survey articles (e.g. Blau and Kahn (2012); Lewis and Peri (2014); Longhi et al. (2005)). More directly connected with this study are recent papers that have analyzed the impact of immigration to Switzerland. These papers however, have mostly reproduced the methodology of studies from the US or other countries in Europe and applied it to Switzerland. Favre (2011) investigates the impact of immigrants along the wage distribution of natives taking the approach first used by Dustmann et al. (2013) to the national level. The paper uses the traditional shift-share instrument as proxy of the exogenous change in immigrants. Favre (2011) shows that newly arriving immigrants are overrepresented at the top of the wage distribution in high-skilled occupations such as management, evaluation and R&D and at the bottom of the wage distribution in low-skilled occupations such as manufacturing, construction, cleaning. Analysing the impacts separately for this two occupation groups, he finds positive effects on wages of natives in the bottom percentiles and slightly negative effects on wages at the top percentiles of high-skilled occupations. In low-skilled occupations, the effects of immigration are slightly positive or close to zero across the entire wage spectrum. Also taking a traditional approach Basten and Siegenthaler (2013) estimate effects across occupation-experience groups. They find no effect on wages and employment of natives in the aggregate but a reduction of unemployment and positive effect on the mobility of natives into higher payed occupations.

Favre et al. (2013) exploit the past distribution of immigrants across commuting zones in the spirit of Card (2001) to estimate the causal effect of immigration between 2002 and 2010 on the employment and unemployment rate of natives with different educational backgrounds. Their results indicate that highly educated workers were slightly negatively affected by the recent immigration wave, whereas the effect on natives with middle or low education was not significantly different from zero.

One paper that tries to exploit the difference in policy implementation between BR and NBR in Switzerland is Losa et al. (2012). The authors only look at the very short-run effect of the liberalization of CBW, by considering a difference in difference between BR and NBR and between 2003 and 2005.[7] These authors control for potential different demand trends across areas by matching BR and NBR municipalities on a large set of observables from the Census 2000. However, they do not investigate pre-1999 trends, nor check the impact of the change in policy on immigrant flows. They simply present a somewhat contradictory negative effect on total employment (-2.4%) and a positive on average wages (+0.8%) of native workers. Interestingly, they also point out that there was substantial geographic heterogeneity across cities, with workers in Basel and Geneva experiencing net wage gains, and those in Zurich and Ticino experiencing no change. The short period considered, the lack of pre-1999 trend tests, the contradictory effect on wages and employment limit the validity of this study.

Finally only few recent papers have analyzed specific immigration policy changes and their impact on economic outcomes. Kerr and Lincoln (2010) and Peri et al. (2014) have considered the change in H1B visa cap (the high skilled immigrants visas in the US) to analyze effects on innovation and productivity in US cities. Bohn et al. (2014) analyzed the impact of Arizona's worker act on undocumented immigrant labor market performance. For Europe Glitz (2012) analyzed the effect of a policy that allowed ethnic Germans in Eastern Europe to obtain German citizenship and this, combined with the end of the iron curtain, generated a sudden inflow of migrants. A handful of additional papers has tried to measure immigration policies and estimate the effects of their changes on immigrant inflows in a multi-country gravity framework. Mayda (2010) and Ortega and Peri (2014) are two examples. In the Swiss context, Abberger et al. (2015) show that the facilitated immigration for EU workers increased their net-inflow by 10'000 to 15'000 individuals yearly. Beerli and Indergand (2014) point out that this policy change also influenced the long-term trends in the skill-mix of immigrants.

2.3 Immigration Policies in Switzerland 1999-2007

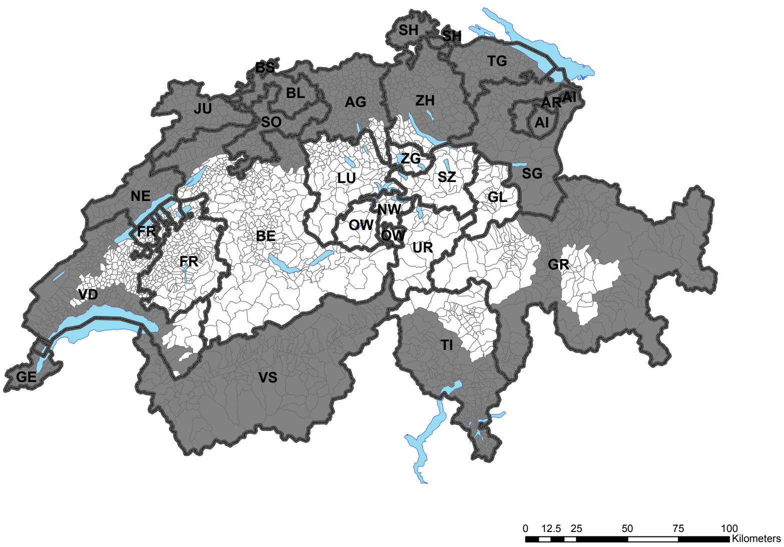
Switzerland rejected with a referendum the proposal to join the European Economic Area in 1992, which would have guaranteed free labor market access to EU citizens. Then, after a series of bilateral negotiations, in June 21, 1999, a package of bilateral agreements (BA I) was signed between Switzerland and the EU which included full bilateral labor market access. Details about the liberalisation process were publicly announced by the federal

[7] In a related study, Bigotta (2013) finds a positive effect of this policy on the unemployment duration of natives.

administration (Bundesrat, 1999) and in 2000, the entire bilateral package was approved with 67.2% by Swiss voters in a nationwide referendum.

The integration of Switzerland into the European labor market involved gradual steps, which was common practice for the accession of new member states to the EU (SECO, 2014). In the case of Switzerland, the transition process was somewhat differentiated for two distinct geographic areas and two different groups of immigrant workers. Due to long-established bilateral agreements with neighbouring countries the group of *cross-border workers* (CBW) who commuted daily across the national border was allowed under special conditions in the *border region* (BR).[8] Prior to 1999, CBWs could obtain a worker permit if no equally qualified native Swiss worker could be found for a given job (the so-called "priority requirement"), yet no numerical cap on their entry existed. CBWs could not work in non-border regions, however. The other group of immigrant workers in Switzerland were the *resident immigrants (RI)* who could work in BR and NBR but the number of their permits was subject to yearly national quotas decided by the federal government. They were also subject to the priority requirement. Figure 2.1 shows a map of Switzerland with the municipalities in the BR shaded in gray color while the remaining ones are in NBR.

Figure 2.1: Municipalities in the Border Region (gray) and in the Non-Border Region (white) and Cantonal Borders



Notes: Municipalities in the border region are indicated in grey and those in the interior region in white. The black lines and letters denote Cantonal borders and abbreviations, respectively. Note that border regions do not overlap completely with cantonal borders.

[8]These bilateral agreements were signed with Italy in 1928, with France in 1946, with Germany in 1970 and with Austria in 1973.

The gradual integration into the the European labor market involved the following time line which is also illustrated in Figure 2.2:

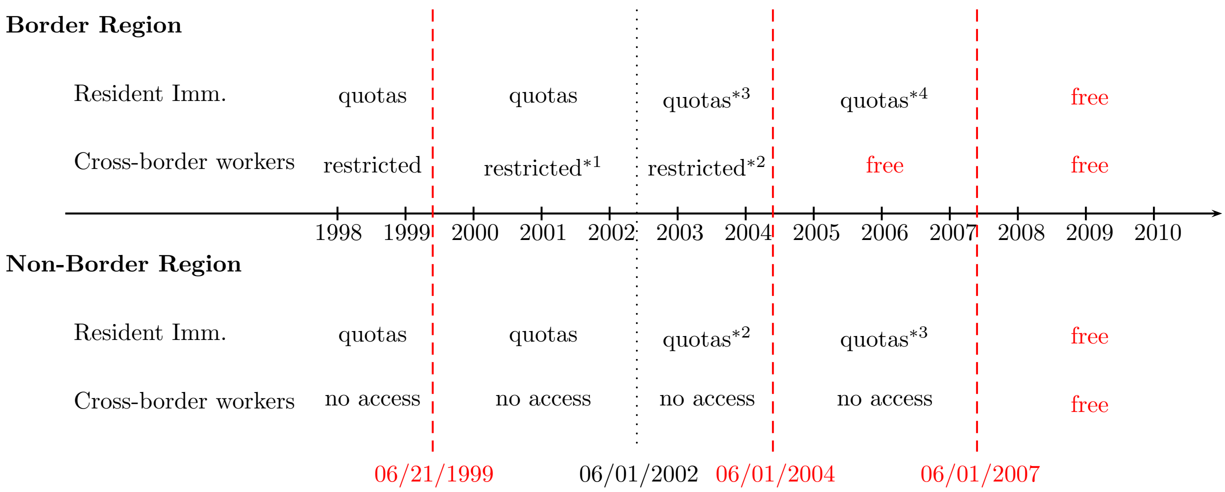
June 21, 1999, signing of bilateral agreements (BA I)

June 1, 2002: Official start of the Agreement of Free Movement of Persons (AFMP)[9]: Cross-border workers were only required to commute back on a weekly basis. Quotas and the 'priority requirement' where still in place for cross-border workers and residing immigrant workers.

June 1, 2004: Abolishment of priority requirement for both types of immigrant workers and full liberalization of access for cross-border workers from EU17 countries to work in the border region.

June 1, 2007: Abolishment of quotas for resident immigrant workers from EU17 and full liberalization of access for CBW in both BR and NBR.

Figure 2.2: Schedule of Labor Market Integration



Notes: *Quotas* for residency permits were set at the federal level and administered by Cantonal immigration offices. *Restrictions* of cross-border worker permits were administered by Cantonal migration offices and not subject to federal quotas.
$*^1$: Less restrictive handling of CBW applications in border cities (e.g. Basel, Geneva) after signing of bilateral agreements on June 21, 1999.
$*^2$: Home commuting requirement for CBW as relaxed from daily to weakly home commuting.
$*^3$: Separate quota for EU and Non-EU citizens resulted in de-facto higher quota for EU citizens compared to years prior to 2002.
$*^4$: Priority requirement of natives abolished.

Figure A.1 in the appendix illustrates in a stylized way the *differential* openness between the BR and the NBR due to the policy changes over the period 1994-2010. During

[9]This resulted in a de-facto larger quota for EU17 citizens compared to before 2002 (SECO, 2014).

the 1994-1999, *pre-policy Phase*, the BR had restricted access to CBW while this type of workers was not allowed in the NBR. In *Phase 1* of the liberalization, 1999-2004, Cantonal immigration offices in the border region progressively gained considerable discretion in allowing labor market access as they could issue working permits for CBW without a quantitative limit.[10] The official start of the Agreement of Free Movement of Persons (AFMP) in 2002 constituted also a step towards more openness of labor market to the circulation of CBW in the BR through the abolishment of the daily commuting condition. Then, in 2004, *Phase 2* of the reform was enacted and the labor markets of BR municipalities became fully open for CBW marking the largest difference in immigrant access to BR while CBW were still not allowed in the NBR. Finally in June 1, 2007, both regions adopted full liberalization for both type of workers and hence they became equal in terms of immigration policies. For RI, which are treated in the same way in BR and NBR, both regions had the same degree of openness between 1994 and 2010.

2.4 Description of Data and Summary Statistics

2.4.1 Data sources and variable definitions

Our main data source is the Swiss Earnings Structure Survey (SESS) which collected demographic and labor market information biannually, from 1994 to 2010, for a representative sample of all Swiss workers.[11] The survey includes the place of work (by zip code) of each worker which we use to map these workers into municipalities using an official crosswalk from the Federal Statistical Office (FSO).[12] Several municipalities in turn can be matched to one of 106 commuting zones (CZs) as defined by the FSO. These zones, matching closely the definition of labor markets, are constructed in a way that municipalities inside a zone have strong commuting ties within and weak commuting ties outside the zone. As described in Section 2.3, each municipality belongs either to the BR or to the NBR.[13] Note that the BR and the NBR do not perfectly overlap with Cantonal borders, as seen in Figure 2.1. As for CZs we define one of them as belonging to the border region if it contains at least one municipality in the border region.

[10] Conversations with representatives of Cantonal immigration offices showed that there was also a more relaxed handling of new CBW applications after 1999.

[11] The Swiss Statistical Office's title of this data-set is 'Lohnstrukturerhebung'. The survey reflects the labor market situation on October 31 of the corresponding year.

[12] As the number of municipalities (and zip codes) is changing over time, mostly through mergers of small municipalities to larger ones, we use the municipality definition of the year 2000 as a stable geographical unit. Observations with out-dated zip codes, which could not be matched (less than 0.3%), were dropped.

[13] We thank Maurizio Bigotta for sharing the data of border region identifiers for each Swiss municipality, cf. Losa et al. (2012) for a description.

Our data include workers between 18 and 65 years old, working in the private sector with non-missing information for nationality, place of work, education, wages and hours. We can distinguish *native workers* (born in Switzerland) from immigrant workers with a short-term residency permit (RI) and cross-border workers (CBW).[14] Combined, we denote the last two groups as *new immigrants* to contrast them with permanent resident foreign-born, which we denote as *earlier immigrants*. A foreign-born can apply for permanent residence only after 5 to 10 years of non-intermitted stay in Switzerland.

A main outcome of the policies that we analyze is the number of new immigrant workers, as share of employment. When considering native and earlier immigrant workers in a municipality/CZ, we measure their total number of hours worked and their wage. The data set contains the gross monthly wage for each individual worker (in the month of October) in Swiss Francs (CHF). This measure includes monthly social transfers, bonuses for the month of October and one twelfth of additional yearly payments and the thirteenth monthly wage. We divide this measure by the number of hours worked in October and use the consumer price index to convert it into *real hourly wage* of an individual worker in 2010 prices. We measure *hours worked* as fractions of the number of hours worked by a full-time worker.

In our regressions we use data aggregated at the area level (either municipalities or commuting zones) and we construct the total regional number of workers and total working hours or the average log hourly wage.[15] In some regressions we first control for individual characteristics and then aggregate the residuals as explained in the data appendix 2.B. As individual demographic controls, we include age, marital status, job tenure (measured as the number of years working for the firm) and education. When separating outcomes by group, we define workers with a tertiary education as being *highly educated*, workers with a completed secondary education as *middle educated* and workers with primary education or less as *low educated*. We use additional information on the *occupation* of each worker and the industry affiliation of worker's the firm.[16]

2.4.2 Summary Statistics and Trends

Table A.1 shows the summary statistics of the characteristics of new immigrants and natives at the national level. Between 1998 and 2010, the number of new immigrants increased by 180'000 workers and their skill composition changed significantly. While in

[14]Technically, resident immigrants hold either a L permit (4 to 12 months) or a B permit (1 to 6 years) whereas cross-border workers hold a G permit.

[15]When analysing wage outcomes, we exclude individuals with wages above the 99th percentile of real hourly wages in each year.

[16]In SESS data, workers are allocated into 23 unique occupation groups.

1998, 85% of the new immigrants were in the lower two education groups, the share of highly educated almost doubled to 30% in 2010. In that year 70% of new immigrants were in the two higher education groups. Overall, the education distribution of new immigrants evolved so that in year 2010 they were over-represented among high and less educated and under-represented among middle educated (a feature shared by immigrants in many rich countries).

Table A.1 shows that in 1998, immigrants were heavily represented in the lowest paid occupations such as hotel, manufacturing and construction. In 2010, these occupations still represent a large fraction of new immigrant employment, yet the largest gains in terms of employment accrued at the top of the wage distribution in analytical jobs, R&D and consultants. Still also some manual jobs such as cleaning had a significant increase in new immigrants.[17]

The appendix tables A.2 and A.3, show two important comparisons. First we present a list of average characteristics of the workforce comparing border and non-border regions in the year 1998. While clearly we include several controls and fixed effects before 1988 to capture differences in the economy of these two types of regions it is useful to notice that in several average characteristics these two regions were similar. The border region have a slightly larger share of highly educated (+2.8 percentage points) and five log point higher wages, while average age, gender shares and labor supply were almost identical between the two regions. Also the sector composition is not too different. Between two to three percentage points differences in the share of manufacturing, finance and business activities (higher in the BR) and in construction, wholesale and restaurants/hotels (larger in the NBR). The lower part of table A.2 shows considerable differences in geographic characteristics. The workforce in the border region is more likely to be situated in a urban areas, less likely to be in mountainous terrain and seven out of the 9 largest cities (with a population larger than fifty-thousand) are located in the border region.[18] Also the border region municipalities have a more prevalently German speaking population than the municipalities in the NBR.

A second useful comparison is between CBW and RI in the border regions in appendix table A.3. We are considering these two groups relatively similar in term of working characteristics. However the summary statistics in appendix table A.3 show that the resident immigrants are somewhat younger and more evenly distributed across education groups than the CBW. Their average wage was, however, similar, and the became also more alike in terms of education by the year 2010.

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[17]This change in the structure of skills of new immigrants was also noted by Beerli and Indergand (2014).

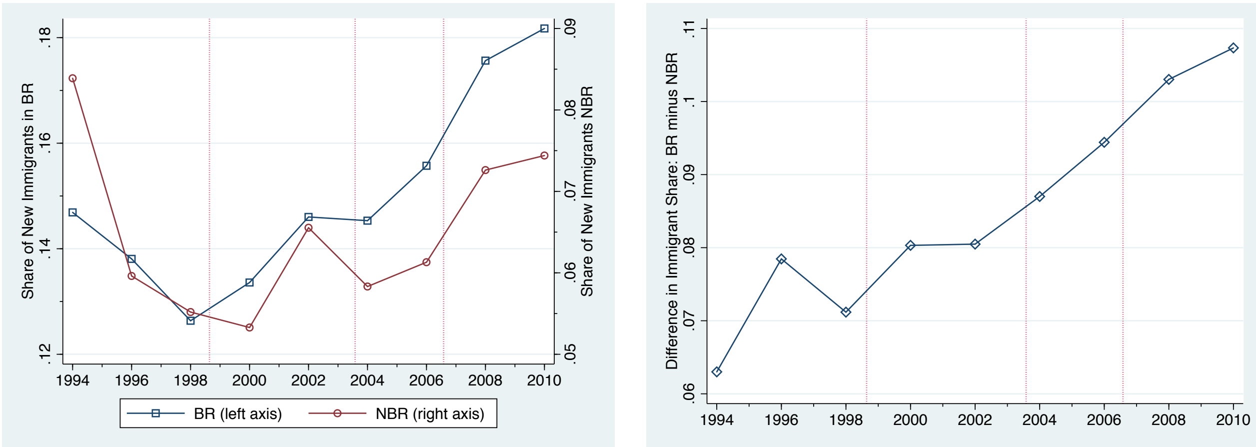
[18]From the nine largest cities Basel, Geneva, Lausanne, Lugano, St.Gallen, Winterthur and Zurich are located in the border region and Lucerne and Bern in the non-border region.

2.5 The Effects of Policies on New Immigrants

We first analyze whether the discontinuous and differential policy changes between the BR and the NBR described in section 2.3 affected the inflow of new immigrants represented by the sum of cross border workers (CBW) and resident immigrants (RI). Policy changes after 1999 increased the openness of the BR (specifically for CBW) relative to NBR in two steps up to 2007, when both regions were fully liberalized. While the specific policies targeted CBW, our first test is whether they changes the total of new immigrants. If they only substituted CBW for RI, leaving the sum unchanged, then the policies did not change the conditions of the BR relative to the NBR. By aggregating the two groups and considering them as close substitutes, we analyze the impact of the policy of 1999, 2004 and 2007 on the pool of new immigrants, in a difference-in-difference approach.

Let us first show the trends and differences in the share of new immigrants between 1999 and 2010. The share of new immigrant increased from 12.6% to 18.2% in the border region and from 5.5% to 7.4% in the non-border region. Hence the presence of new immigrants as share of employment increased by roughly 3.6 percentage points more in the border region than in the non-border. The evolution of this difference is plotted in the right panel of Figure 2.3 while the left panel shows the evolution of the shares in each region. The difference shows that before 1999 the difference in employment share of new immigrants between the BR and the NBR had a jagged evolution, while after 1999 it shows a consistent growth especially during the 2004-2008 period which includes the full liberalization of the BR. Two observations are in order. First the pre-1999 trend is rather noisy, but possibly positive so that it will be important to control for pre-existing characteristics. Second, after 2007 the positive differential trend continues, probably due to inertia in migration. We will analyze both points more formally below. The important visual impression from Figure 2.3 is that a differential trend between BR and NBR in new immigrants as share of employment seems to arise in 1999 and strengthen after 2004.

Figure 2.3: Evolution of the Share of New Immigrants (Left Panel) and the Difference in New Immigrant Shares Between Border and Non-Border Region (Right Panel)



Notes: New immigrants are the sum of cross-border workers and resident immigrants. The left panel plots the evolution of the share of new immigrants on the total workforce in the border region (left y-axis) and the same share in the non-border region (right y-axis). The right panel plots the difference in the share of new immigrants between both regions, $(IM_{BR,t}/TOTEMP_{BR,t}) - (IM_{NBR,t}/TOTEMP_{NBR,t})$. Vertical lines indicate June 21 1999, when the agreement was signed, June 1 2004, when the labor markets of the border region and the non-border were liberalised differentially, and and June 1 in 2007, when the differential openness of the border region ended. Note that years indicate the labor market situation by October 31 of the corresponding wave.

2.5.1 Differential Trends in the Share of New Immigrants

To investigate this effect more rigorously, we run the following difference-in-difference regression:

$$\frac{IM_{m,t}}{TOTEMP_{m,t}} = \alpha_m + \alpha_t + \beta_1 \left[BR_m \times D^{2004}_{2000}\right] + \beta_2 \left[BR_m \times D^{2010}_{2004}\right] + X'_{m,t}\gamma + \epsilon_{m,t} \quad (2.1)$$

where $\frac{IM_{m,t}}{TOTEMP_{m,t}}$ is the share of new immigrants on the total workforce in area m and year t. Areas are either municipalities or commuting zones. The dummy BR_m is one for areas located in the border region and the dummies D^{2004}_{2000} and D^{2010}_{2004} indicate the years 2000 and 2002 and 2004 to 2010, respectively. α_m is an area fixed effect absorbing all constant area differences including the difference between border and non-border region, i.e. the main effect, as well as differences in initial sector specialisation, differences in geography, area size, institutions or languages. α_t absorbs common yearly fluctuations. If immigrant exposure increases differentially in areas in the border region after the announcement of the differential policy treatment, we would expect that $\beta_1 > 0$. Conversely, we would expect that $\beta_2 > 0$ if immigrant inflow is different after legislatory changes were implemented.

Table 2.1 presents estimates of equation (2.1) on the municipality (columns 1-3) and on the commuting zone level (columns 4-6). In all specifications, standard errors are clustered on the Cantonal level and cells are weighted with its total workforce. Column 1 (column 4) shows estimates with time fixed affects only whereas column 2 (column 5) also accounts for municipality (commuting zone) fixed effects. The estimate of the main effect, BR_m, shows that the pre-policy difference in immigrant exposure was roughly 7 percentage points. This difference is estimated to increase by roughly 1 percentage point during Phase 1 of the policy change and by roughly 2.7 percentage points in the period after 2004 in Phase 2. In general, estimates change very little across specifications and area levels. These reform effects are jointly highly significant and the effect in the second period is significantly different from the effect in the first period, which suggests that policy changes introduced in 2004 were most important for the inflow of immigrants.

The interpretation of β_1 and β_2 as policy effects relies on the identifying assumption that there are no omitted time-varying effects with a differential impact across regions. One important concern is that industry-driven, local labor demand shocks could be correlated with the inflow of newly arriving immigrants. For instance, the trade liberalisation introduced in some industries after 2002 through the same bilateral agreements with the EU could have affected regions differentially to the degree of their pre-existing industrial structure.[19] Although this part of the bilateral agreement did not feature a differential treatment between border and non-border region, it is important that we account for differential industry-specific demand shocks. To control for these shocks, we include a measure of labor demand shifts based on an area's industry composition in 1994.[20] The basic idea is that industry-specific demand shocks at the national level affect regions differentially to the degree these regions specialise in the production of different goods. If employment in given industry increases (decreases) nationally, regions where that industry employs a significant share of the total labor force will experience a positive (negative) shift to the demand for workers. We define the sector-driven employment level for group G in a commuting zone m in year t as

$$\widetilde{EMP}^{G}_{m,t} = \sum_{i \in \{1,50\}} \left(EMP^{G}_{i,m,1994} \times \frac{EMP^{G}_{-m,i,t}}{EMP^{G}_{-m,i,1994}} \right) \tag{2.2}$$

where $EMP^{G}_{i,m,1994}$ is the employment level of group G in commuting zone m and (2 digit) industry i in the first available wave 1994 and $\frac{EMP^{G}_{-m,i,t}}{EMP^{G}_{-m,i,1994}}$ is the employment

[19]Bühler et al. (2011) estimate that trade liberalisation through the bilateral agreement with the EU increased the growth of plants in affected industries in Switzerland by 1-2 percent between 2002 and 2008.

[20]This controls was initially proposed by (Bartik, 1991) and Blanchard and Katz (1992) and found wide application in the literature, e.g. Autor and Duggan (2003); Notowidigdo (2011); Peri et al. (2014).

growth factor between 1994 and year t in this industry nationally.[21] Following the literature we sometimes call this imputed demand-shifter "Employment Bartik Instrument" for employment growth, following Bartik (1991). In columns 3 and 6 of table 2.1, we include the logarithm of $\widetilde{EMP}^{Total}_{m,t}$ with the total employment. Local, industry-driven employment tends have considerable power in predicting immigrant employment, slightly increase the magnitude and the precision of the estimated policy effect.[22] This suggests that the estimated policy effect are not upwardly biased by omitted demand shocks. In what follows, we want to gain more confidence in this finding.

Table 2.1: Difference-in-Difference Analysis of the Effect of the Opening on the Share of New Immigrants on Total Employment

Dependent variable: Share of new immigrants on total employment

Area level	Municipality			Commuting zone		
	(1)	(2)	(3)	(4)	(5)	(6)
$BR_m \times D^{2004}_{2000}$	0.00950	0.00904	0.0113	0.00927	0.00982	0.0120
	[0.00468]*	[0.00539]	[0.00515]**	[0.00447]**	[0.00497]*	[0.00477]**
$BR_m \times D^{2010}_{2004}$	0.0274	0.0265	0.0295	0.0281	0.0282	0.0309
	[0.00997]**	[0.0102]**	[0.00964]***	[0.00981]***	[0.0101]**	[0.00958]***
BR_m	0.0709			0.0732		
	[0.0277]**			[0.0273]**		
$\ln \widetilde{EMP}^{Total}_{cz,t}$			0.154			0.138
			[0.0585]**			[0.0600]**
Year fixed effects	√	√	√	√	√	√
Area fixed effects		√	√		√	√
Observations	12,801	12,801	12,795	948	948	945
R-squared	0.117	0.850	0.852	0.163	0.943	0.945

Notes: ***, **, *, denote statistical significance at the 1%, 5% and 10% level, respectively. Robust standard errors, clustered by Canton, are given in parentheses. BR_m is one for municipalities (commuting zones) in the border region. D^{2004}_{2000} and D^{2010}_{2004} are dummies for the differential opening in *Phase 1*, from 1999 to 2004, and *Phase 2*, from 2004 to 2010, respectively. Regressions are weighted using the total workforce of cells.

[21] Here, group G is total employment, later, e.g. in section 2.7 we will use education group specific Bartik measures. To avoid spurious correlation, we exclude each commuting zone's own industry employment in the calculation of the growth factor. Note that we can only construct meaningful Bartik controls on the commuting zone level, as the sample size is simply too small on the municipality level. In the regression, we use Bartik controls on the level of commuting zones in both CZ and municipality specifications. We dropped the industries 'Recycling', which were not available in all years.

[22] The influence of local demand has also been highlighted by Beerli and Indergand (2014) who show that the immigrant composition in terms of skills at the local responds strongly to skill-biased local demand shifts.

2.5.2 Robustness and Instrument Validity

Pre-Trend Analysis

The identification strategy used in equation (2.1) can be generalised to an interaction term analysis to investigate pre-trends. Consider the following specification

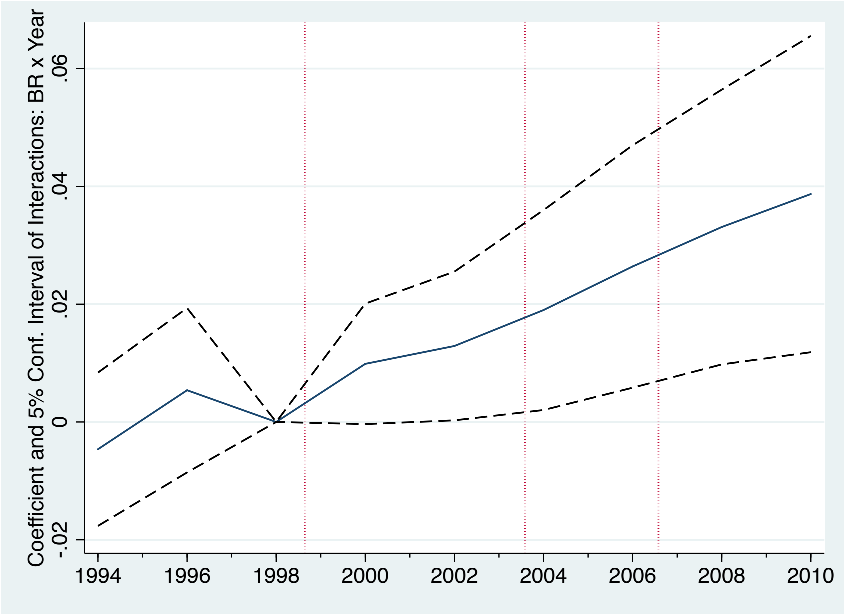
$$\frac{IM_{m,t}}{TOTEMP_{m,t}} = \alpha_m + \alpha_t + \sum_{t=1994}^{1996} (\gamma_t \cdot BR_m \times D_t) + \sum_{t=2000}^{2010} (\beta_t \cdot BR_m \times D_t) + X'_{m,t}\delta + \epsilon_{m,t} \quad (2.3)$$

where D_t is a dummy for each year in our panel except the last year before the on-set of the policy change, 1998. This unrestricted estimation measures the time dimension of the differential opening policy relative to the base year 1998 just before the policy change was initiated.[23] The coefficient γ_t and β_t can be interpreted as estimates of the impact of the policy in a given year. Clearly, there is a testable restriction on the pattern of these estimates. The estimated impact of the policy should be zero prior to the date when it was announced, i.e. $\gamma_t = 0$, and start increasing after 1999, $\beta_t > 0$.

Figure 2.4 plots the coefficient, γ_t and β_t, and the 5% confidence interval of an estimate of equation (2.3) on the municipality level including the Bartik control. These coefficients fluctuate around zero prior to 1999, start to become significantly different from zero after 2000 and show an up to 4 percentage point difference in immigrant exposure in the border region by year 2010. This shows that trends in immigrant exposure were not significantly different between the border and non-border region prior to the differential opening policy but started to differ after its signing and announcement in 1999 and became most pronounced with its implementation in 2004. For completeness, appendix table A.5 reports the coefficients estimates of equation (2.3) on the municipality and commuting zone level with varying controls.

[23] Note that the results are very similar if we omit the year 1996 instead.

Figure 2.4: Plot of Coefficients and 5%-Confidence Interval of the Year Analysis of the Evolution of the Share of New Immigrants (Equation (2.3), Base Year = 1998)



Notes: The figure plots coefficients (straight line) and the 5%-confidence interval (dashed lines) of an estimate of equation (2.3) including municipality and year fixed effects ant the Bartik control, shown in column 3 of appendix table A.5. Vertical lines indicate June 21 1999, when the agreement was signed, June 1 2004, when the labor markets of the border region and the non-border were liberalised differentially, and and June 1 in 2007, when the differential openness of the border region ended. Note that years indicate the labor market situation by October 31 of the corresponding wave.

Effect of Openness on Growth of the Number of New Immigrants

A more demanding specification to analyze the effect of Phase 1 and 2 of the reforms is to see if they had a differential impact on growth of new immigrants as share of employment, rather than their levels, after controlling for common trends. Analyzing new immigrant growth instead of levels across time and regions and controlling for time and region effects has the advantage of differencing out fixed regional factors and controlling for regional trends. Figure A.2 in the appendix shows that the the growth of newly arriving immigrants (left panel) and its difference between border and non-border region (right panel). Indeed, the growth of immigrants does not exhibit a systematic difference prior the differential opening but seems to be larger in the border region in the first two-year interval starting in 1998 and become more pronounced after 2002. We can also investigate this more systematically by running counterparts of equation (2.1) and equation (2.3) with immigrant growth:

$$\frac{\Delta_t^{t+2} IM_m}{TOTEMP_{m,t}} = \alpha_m + \alpha_\tau + \beta_1 \left[BR_m \times D_{1998}^{2004}\right] + \beta_2 \left[BR_m \times D_{2004}^{2010}\right] + X'_{m,\tau}\gamma + \epsilon_{m,\tau} \quad (2.4)$$

$$\frac{\Delta_t^{t+2} IM_m}{TOTEMP_{m,t}} = \alpha_m + \alpha_\tau + \gamma \left[BR_m \times D_{1994}^{1996}\right] + \sum_{t=2000}^{2010} (\beta_t \cdot BR_m \times D_t^{t+2}) + X'_{m,\tau}\delta + \epsilon_{m,\tau} \quad (2.5)$$

where $\frac{\Delta_t^{t+2} IM_m}{TOTEMP_{m,t}}$ is the biannual change in the number of newly arriving immigrants in area m normalised by its total workforce at the beginning of the period τ. α_m account for area specific trends in those growth rates and α_τ absorb period fluctuations. β_1 and β_2 in equation (2.4) estimate whether the growth in the number of newly arriving immigrants is significantly different in areas in the border region in period after the announcement of the differential opening from 1998 to 2004 or after the differential opening 2004 to 2010, respectively. We control for industry-driven demand shocks in a similar fashion as above by including the growth version of the Bartik on the commuting zone level.[24]

Table A.6 and table A.7 present the estimates of the coefficients specified in equation (2.4) and (2.5), respectively. As in the previous tables we show the estimates using municipalities (columns 1-3) and commuting zones (columns 4-6) as units of observation and the different columns show estimates including only the BR dummy as control (specifications 1 and 4) including also area fixed effects (specifications 2 and 5) and including the Bartik control (Specifications 3 and 6). The difference-in-difference analysis in Table A.6 shows that the BR-NBR differential in immigrant growth as share of employment, was significant only in the period of the reform implementation, after 2004. In this specification, controlling for a common trend in immigrant shares, the significant change is observed only during the period of actual liberalization of CBW mobility for the BR. The year analysis in table A.7, for which figure A.3 plots the estimates in column 3, confirms one important feature of the data and introduces a new fact. First, the BR-NBR difference in immigrant growth was not significantly different prior to the policy announcement,

[24]The growth version of the Bartik measures the average industry growth on the national level (excluding the growth of a commuting zone) weighted by the commuting zone's 1990 industry composition:

$$\left(\frac{\widetilde{\Delta_t^{t+2} E_m^G}}{TOTEMP_{m,t}}\right) = \sum_{i\in\{1,50\}} \left(s_{i,m,1990} \times \frac{\Delta_t^{t+2} E_{-m,i}^G}{TOTEMP_{-m,i,t}}\right)$$

where $s_{m,i,1990}$ is the share of each (2 digit) industry i on total employment in commuting zone m in 1990. $\frac{\Delta_t^{t+2} E_{-m,i,t}^G}{TOTEMP_{-m,i,t}}$ is change in education of group $G \in$ {all, high, middle, low} in industry i at the national level (excluding region m) between t and $t+2$ divided by industry total employment in year t. G is either the total native workforce or natives separated by education group.

(1994 to 1996) relative to the omitted period (1996 to 1998). After the signing of the agreement in 1998 the difference was still insignificant up to 2002. Only beginning in the period from 2002 to 2004 the BR had a faster growth of immigrants, even controlling for area-specific trends and common yearly trends. In each biennium, new immigrants grew, as percentage of total employment, by 2.2 percentage points more in the BR relative to the NBR. The last period considered in our analysis which is the biennium, 2008-2010 is a period in which the policy differential between BR and NBR have been eliminated as all regions enjoy fully open borders with the EU. While we see that the differential in growth of new immigrant share is a bit reduced, we do not observe a full reversal to zero. The fact that immigrant networks persist and the dynamic complementarity of immigrants may continue to show effects also under free mobility may be a reason for not observing a greater reduction of differential after both regions have been opened. Due to the short period of data available to us, after 2007 it is hard to say whether the ‘‘first mover's advantage’’ of the BR gave them a long-lasting lead in attracting immigrants.

Effect of Policy at the Border Between Regions and Accounting for Regional Heterogeneity

As shown in section 2.4.2, the border and non-border regions area rather similar in terms of their demographic characteristics, distribution of age and schooling across workers, and in terms of their industrial structure. However, they exhibit some heterogeneity in terms of geography: The border region is more urban, less mountainous and closer to the international border of Switzerland. In this section we explore some geographical aspects of the regions further: On one hand we investigate the robustness of the effects to geographical controls, on the other we look for further insight on how geography affected the outcomes of the immigration reforms.

First, we can gain additional confidence in our baseline estimates, repeated in column 1 of appendix table A.8, by examining their robustness with respect to a couple of alternative checks for differential demand shocks. In column 2, we interact a municipality's employment level in 11 different 1-digit industries in 1990 with linear trends (and their squares and cubics) instead of using the Bartik measure.[25] This reduces both coefficients to some degree but still leaves the coefficient of the period from 2004 to 2010 significantly

[25]We calculate the total number of workers in 11 different 1-digit industries using data from the national Census in 1990, which provides a full count of the working population. Specifically include the following regressors in our regressions: $\sum_{i=1}^{11} \gamma_i^{linear} \left(EMP_{m,1990}^{Industry=i} \times trend_t \right) + \sum_{i=1}^{11} \gamma_i^{quadratic} \left(EMP_{m,1990}^{Industry=i} \times trend_t^2 \right) + \sum_{i=1}^{11} \gamma_i^{cubic} \left(EMP_{m,1990}^{Industry=i} \times trend_t^3 \right)$.

different from zero.[26] In column 3, a very important robustness check, accounts, as best as we can, for the geographic differences of municipalities in both regions. In this specification we restrict the sample to include only those BR and NBR municipalities located next to a municipality from the other region (BR for NBR and NBR for BR). namely this regression compares only municipalities that are next to each other and which share the same geography and, likely, market condition. This reduced the sample size drastically, but yields almost identical point estimates. This reduced the sample size drastically, but yields almost similar estimates.[27] Then, in specification 4, we drop the seven largest municipalities in the border region, eliminating the large urban centres and restricting the comparison across regions between municipalities with a very similar average workforce size.[28] Again, the estimates are almost unchanged.[29]

Next, we explore whether there is some important heterogeneity of the effects of the policy across different type of areas. Columns 5 and 6 restrict the sample in both BR and NBR to be, alternatively, only urban and only rural municipalities, respectively. On one hand, this comparison increases the homogeneity of labor markets on the two sides. On the other, it allows to identify which type of municipalities responded more to the policy. The coefficient estimates show that the differential change in immigrant share is only apparent when we consider urban locations on both sides of the policy regions. Likely the more active labor markets of the urban BR were those in which large part of the policy has produced its effect. The policy could also interact with pre-existing amenities to produce differential effect in the "treated group". In particular distance to the international border between Switzerland and other EU countries might have considerable influence on the location decisions of immigrants and hence for a given policy, municipalities near the international border might have received stronger "treatment" (i.e. immigrant inflow).[30] Column 7 to 10 compare municipalities in the border region within several distance bins from the national border to the entire control group of non-border region municipalities. This evaluation shows that change in immigrant exposure was to some degree larger (al-

[26] In addition, we cannot reject the hypothesis that this effect for Phase 2 is similar to the baseline specification. Similar results are found for interactions of a municipalities 1-digit sector share in 1990 with (linear, quadratic and cubic) trends or interactions of log employment with these trends.

[27] We obtain a similar estimate if we constrain the sample to include only municipalities which are within 10 minutes driving time from the other region. This selects even fewer municipalities at the border between both regions where this border does not coincide with a natural barrier, such as a lake or a mountain ridge.

[28] Specifically, the average total workforce is 846 workers in the border region and 852 in the non-border region in contrast to 1214 and 852 without dropping.

[29] This is very similar to dropping instead the (e.g. top 10) municipalities with the largest 1990 employment (or share) in the financial industry to account of the fact that differential demand trends could be driven by different exposure to an expanding financial sector.

[30] Several papers show that a common language and distance are important for the location decision of immigrants conditional on local labor demand, see e.g. Grogger and Hanson (2011) and Mayda (2010).

though not significantly so) among municipalities close to the national border. It also shows that considering BR municipalities closest to the Swiss international border, the impact of Phase 2 of the reform was particularly strong. Finally, columns 11-13 show the differential effect separately estimated for different linguistic areas of Switzerland in the treatment group (the BR). These specifications show that the French-speaking municipalities in the border region experienced the largest change in immigrant exposure (6.4 percentage points in the Phase 2), followed by the Italian/Romansh-speaking part (3 percentage points), while change in the German-speaking part cannot be distinguish from zero. Overall the robustness checks emphasize that the impact of reforms on immigrant share is robust and diffused to all BR municipalities (using NBR ones as control), although with different intensity. It was the strongest in urban municipalities, close to the international border in the French speaking area.

We do a final check, to test that the policy discontinuity in the two types of regions is an important driver of the trends in new immigrant exposure by examining these trends when we literarily approach the border between both regions where other determinants of immigrant inflow vanish. This idea is illustrated in Figure 2.5 which plots the change in immigrant exposure for different years since 1998 for municipalities which are in 30 minutes commuting time to the other region.[31] Circles to the left of zero, with negative distance, represent municipalities in the non-border region whereas circle to the right represent municipalities in the border region. The straight line is an estimate of the average change in immigrant exposure depending on the commuting time from a municipalities to closest municipality in the other region. The dashed lines are the 10% confidence interval of this estimate.[32] We would like to know whether there is a discontinuity in these trends as we approach the border between both regions, especially after Phase 1, when the differential openness of both region became most pronounced. This is exactly what we find. Panel A shows that the change in immigrant exposure from 1998 to 2002 was not different from zero on either or the other side. This changed the first time in 2004 (Panel B), when the border region was completely liberalised while the non-border region was not. In this

[31]The estimate of the border region intercept is not sensitive to this sample selection. Similar results were obtained using only municipalities in commuting zones bordering the border between both regions or using longer commuting distances to this border.

[32]Specifically, we estimate the follow specification

$$\Delta^t_{1998}\left(\frac{IM_m}{TOTEMP_m}\right) = \alpha^t + \beta^t_1 BR_m + \beta^t_2 distance_m + \beta^t_3 distance_m \times BR_m + \epsilon_{m,t}$$

where $distance_m$ represents the shortest commuting time (by car) from each municipality to the closest municipality on the other side of the border between the border and the non-border region. We restrict the sample to include only municipalities within 30 minutes commuting time to this border. β^t_1 is an estimate of the discontinuity in the change in average immigrant exposure between 1998 and year $t \in \{2002, 2004, 2010\}$ at the border between both regions.

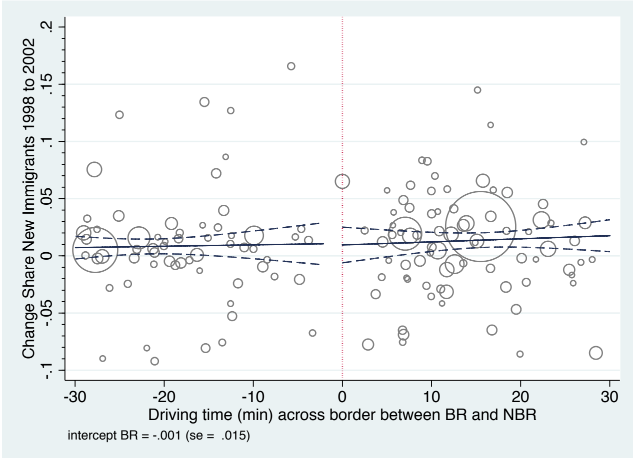
period, immigrant exposure increased significantly in the border-region municipalities while the change in municipalities in the non-border region is not different from zero. Furthermore, the estimated discontinuity at the border between both regions is roughly 2 percentage points and significant.[33] Panel C of figure 2.5 shows that by 2010, after free mobility was also adopted in the non-border region, immigrant exposure changed there as well relative to is own level in 1998 but the difference (at the border) between both regions remained more or less intact.[34] Thus, this analysis reveals that there is some persistence in the effect of the differential opening even after both regions became legally similar open which is due to head-start in the implementation of the free movement policy for municipalities in the border region.

[33]The magnitude of estimate is robust the the exclusion of the largest municipality, Zurich, in the border region.

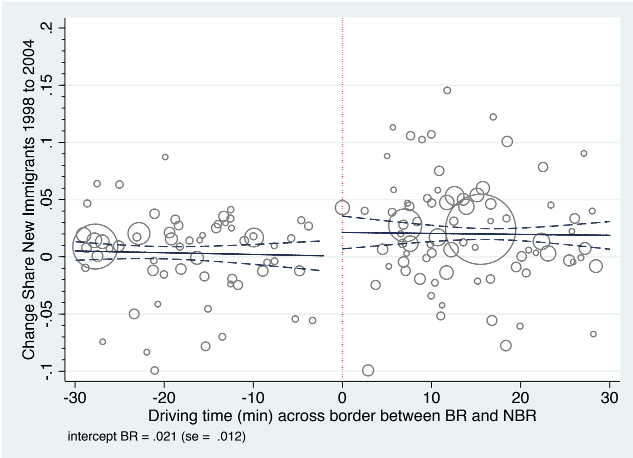
[34]The hypothesis that the difference at the border between both regions remains similar as in the period 1998 to 2004 also in later periods cannot be rejected.

Figure 2.5: Change in the Exposure to New Immigrants Relative to 1998 at the Border between the Border Region and the Non-Border Region, for Different Periods

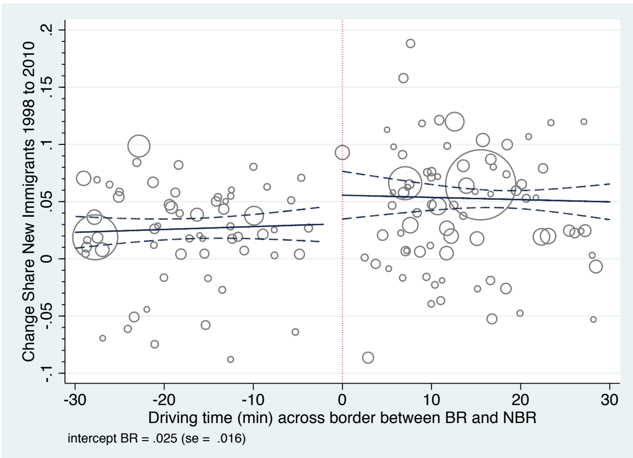
A. Change in share of new immigrants between 1998 and 2002



B. Change in share of new immigrants between 1998 and 2004



C. Change in share of new immigrants between 1998 and 2010



Notes: Scatterplot of change in immigrant share between 1998 and specified year of each municipalities against commuting time to the border between BR and NBR. Only municipalities within 30 minutes commuting time with positive (negative) distance values for municipalities in the BR (NBR). The size of the circle reflects the workforce size in 1998. The straight (dashed) lines represent the predicted average change in immigrant exposure (10% confidence interval) from the following model for year t: $\Delta^t_{1998}\left(IM_m/TOTEMP_m\right) = \alpha^t + \beta^t_1 BR_m + \beta^t_2 distance_m + \beta^t_3 distance_m \times BR_m + \epsilon_{m,t}$. An estimate of β^t_1 is shown below each figure. Municipalities with total employment below 1000 workers are not plotted but included in the regressions. See section 2.5.2 for more details. SESS data. Distance data are taken from search.ch map data.

2.6 Effects on Natives

2.6.1 Aggregate Effects

The Reform Effect on Average Hourly Wages

Proving that the Swiss policy reforms at hand had a noticeable impact on new immigrants implies that we can use their differential change across regions to analyze the consequences on native workers. To analyse this question we first use the same identification strategy as in the previous section and we run a difference-in-difference specification of native outcomes, within a regression framework:

$$y^G_{m,t} = \alpha_m + \alpha_t + \beta^G_1 BR_m \times D^{2004}_{2000} + \beta^G_2 BR_m \times D^{2010}_{2004} + X^{G,\prime}_{m,t}\gamma + \epsilon_{m,t} \tag{2.6}$$

where $y^G_{m,t}$ is the the outcome of interest measured for group G, usually the total of native or earlier immigrant workers or a subgroup of those, in area m and year t. The estimate of β^G_1 and β^G_2 show whether outcomes for group G *changed differentially* in the BR relative to the NBR in Phase 1 or Phase 2 of the policy reforms. The first outcome variable that we consider is the logarithm of hourly wages. The interpretation of β^G_1 and β^G_2 as effects of the policies hinges on the identifying assumption of no omitted time-varying region-specific effects correlated with the policy. As before, we use year and area fixed effects and also we include specifications including other controls such as a wage specific Bartik index and other demography controls.[35]

The results of this reduced form estimation specified in equation (2.6) are reported in table 2.2 for average log hourly wages of natives (Panel A) and earlier immigrants (Panel B). In parenthesis under the estimates, we report robust standard errors clustered at the Cantonal level. Columns 1 to 4 show estimates on the municipality level and columns 5 to 8 on the level of commuting zones. In Column 1 (column 4), we start out with year and area fixed effect only and successively switch in Bartik controls in column 2 (column 5) and

[35] We construct a separate Bartik measure for wage outcomes as follows:

$$\widetilde{w_{m,t}} = \sum_{i \in \{1,50\}} s_{i,m,1990} \left(w^G_{i,m,1994} \times \frac{w^G_{-m,i,t}}{w^G_{-m,i,1994}} \right)$$

where $w^G_{i,m,1994}$ is the initial, average log hourly wage payed in (2-digit) industry i of workers in education group $G \in$ {all, high, middle, low} (where 'all' means aggregate employment) in location m in the first available wave in 1994 and $\frac{w^G_{-m,i,t}}{w^G_{-m,i,1994}}$ measures industry wage growth for that group on the national level (excluding area m). Wage growth is aggregated using each industry's employment share in 1990 $s_{m,i,1990}$ taken from the national Census. We use the employment shares from the Census rather than from the first wave in the SESS as the Census represents a full count of the working population. Using SESS data to construct these shares yields very similar results.

average demographic area characteristics in column 3 (column 6).[36] In column 4 (column 8) we use an alternative way of controlling for individual demographic characteristics. We use an 'adjusted' wage measure, which has been purged of individual level demographic characteristics before averaging at the area level.[37] The table shows robust and relatively precisely estimated results. All point estimates are very close to zero, never larger than one percentage point and not statistically different from zero. Neither in Phase 1 nor in Phase 2 of the reform did native wages experience any significant change. A test for joint significance of both β_1^G and β_2^G is rejected for all columns at the 5% level and only maintained for the specification in column 8 for natives at the 10% level. In the case of natives the estimated effects range, for Phase 2, between one tenth of a percentage point and one percentage point and are always very far from statistical significance.

Table 2.2: Difference-in-Difference Analysis of the Effect of the Opening on Average Log Hourly Wages of Natives and Earlier Immigrants

Area level	Municipality				Commuting zone			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	A. Dependent variable: Average log hourly wages of natives							
$BR_m \times D_{2000}^{2004}$	-0.00239	-0.00240	0.00220	0.00161	0.00110	0.00104	0.00406	0.00503
	[0.00610]	[0.00623]	[0.00536]	[0.00591]	[0.00716]	[0.00722]	[0.00468]	[0.00538]
$BR_m \times D_{2004}^{2010}$	-0.00839	-0.00668	-0.00310	-0.00469	-0.00869	-0.00745	-0.000961	-0.00638
	[0.0125]	[0.0102]	[0.00538]	[0.00576]	[0.0120]	[0.00978]	[0.00385]	[0.00549]
Observations	17,664	17,654	17,480	17,535	949	945	945	945
R-squared	0.761	0.762	0.860	0.754	0.920	0.920	0.963	0.933
	B. Dependent variable: Average log hourly wages of earlier immigrants							
$BR_m \times D_{2000}^{2004}$	0.00278	0.00241	-0.00295	-0.00212	0.00419	0.00373	-0.00463	-0.00172
	[0.00770]	[0.00758]	[0.00423]	[0.00407]	[0.00694]	[0.00677]	[0.00378]	[0.00456]
$BR_m \times D_{2004}^{2010}$	0.0100	0.00759	-0.00367	-0.00382	0.00970	0.00603	-0.00442	-0.00467
	[0.0122]	[0.0110]	[0.00774]	[0.00768]	[0.0114]	[0.0101]	[0.00685]	[0.00681]
Observations	12,796	12,790	12,541	12,629	948	945	945	945
R-squared	0.624	0.624	0.788	0.563	0.846	0.848	0.920	0.821
Year/Area fixed effects	√	√	√	√	√	√	√	√
Bartik		√	√	√		√	√	√
Demo. controls			√	Adj. $y_{m,t}$			√	Adj. $y_{m,t}$

Notes: ***, **, *, denote statistical significance at the 1%, 5% and 10% level, respectively. Robust standard errors, clustered by Canton, are given in parentheses. BR_m is one for municipalities (commuting zones) in the border region. D_{2000}^{2004} and D_{2004}^{2010} are dummies for the differential opening in *Phase 1*, from 1999 to 2004, and *Phase 2*, from 2004 to 2010, respectively. Regressions are weighted using the total workforce of cells.

In sum, this means that we can not find clear evidence that average wages increased less in the border region during the time of the differential opening.

[36]We control for each area's biannual share of male, married, highly and middle educated workers as well as for average age and tenure and their squares.

[37]Specifically, we regress each individuals log hourly wage on very flexible form of individual, demographic characteristics following what is done in Card (2001). Details of this procedure are explained in the data appendix 2.B.

The Causal Effect of Immigration on Average Hourly Wages

Under the assumption that the evolution of wages would not have been evolved systematically different from one region to another in the absence of the differential opening, we can estimate the impact of the opening policy (Duflo, 2001). In addition, if we assume that the differential opening of the border region had no effect on the outcomes of natives or earlier immigrants other than through changing immigrant exposure, we can use this to construct instrumental variables estimates of the impact of immigration on labor market outcomes of natives and earlier immigrants. In this case, estimates of equation (2.1) represent the first stage of a two-stage least square estimation of the impact of immigrants on group specific outcomes. Then, we can consider the following equation to estimate the causal effect of immigration on group outcomes:

$$y^G_{m,t} = \alpha_m + \alpha_t + \delta^G \left(\frac{IM_{m,t}}{TOTEMP_{m,t}} \right) + X^{G,\prime}_{m,t}\pi + \eta_{m,t} \tag{2.7}$$

where $\frac{IM_{m,t}}{TOTEMP_{m,t}}$ represents the share of immigrant workers on the total working population in area m and year t. Estimating equation (2.7) with ordinary least-square may lead to biased estimates if there is correlation between $\eta_{m,t}$ and $\frac{IM_{m,t}}{TOTEMP_{m,t}}$. However, under the two assumptions outlined above, i.e. no omitted time-varying confounders and the exclusion restriction, we can use the interactions between the post-1999 period and the border region identifier as instruments for immigrant exposure in equation (2.7). Then, estimates of δ^G represent the causal effect of immigrant exposure on labor market outcomes of existing groups of workers.

The results of this 2SLS estimation for log hourly wages of natives (Panel A) and earlier immigrants (Panel B) are presented in table 2.3. The columns in this table are similarly organised as in e.g. table 2.2 showing specification on the municipality (commuting zone) level controlling for fixed effects only in column 1 (column 5), including the wage Bartik in column 2 (column 6), including in addition demography controls in column 3 (column 7) or using the adjusted wage measure to control for demographic characteristics in column 4 (column 8).[38] The first row in each panel shows the OLS estimates. These estimates are usually positive but not significantly different from zero for natives and slightly positive and significant for earlier immigrant on the commuting zone level. The second row presents the 2SLS estimates of equation (2.7) using two interaction terms, $BR_m \times D^{2004}_{2000}$ and $BR_m \times D^{2010}_{2004}$, as instruments for $\frac{IM_{m,t}}{TOTEMP_{m,t}}$. In the third row, we collapse these two interaction terms to just one interaction for the entire period, $BR_m \times D^{2010}_{2000}$, and use this as a single instrument. The first stage F-statistics, reported below the standard errors in

[38] Note that we include both the wage and the employment Bartik in this IV regression. Using only the wage Bartik yields very similar results but reduces the power of the first stage to a small degree.

each row in round brackets, shows that the latter strategy yields a reasonably powerful instrument with all values close to Stock et al. (2002)'s threshold of 10. Most of the IV estimates are below their OLS counterparts but still not significantly different from zero. This indicates that OLS estimates are biased upward to some degree. This could be driven by the tendency of immigrants to settle in prosperous areas which would produce a positive correlation between immigrant inflows and contemporaneous labor market conditions.

Table 2.3: OLS and 2SLS Estimates of the Effect of New Immigrants on Average Log Hourly Wages of Natives and Earlier Immigrants

Area level		Municipality				Commuting zone			
Method	Instrument(s)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		A. Dependent variable: Average log hourly wages of natives							
OLS		0.0192	0.0174	-0.00886	-0.000775	0.192	0.196	0.0366	0.0383
		[0.0636]	[0.0638]	[0.0311]	[0.0331]	[0.144]	[0.153]	[0.0556]	[0.0857]
2SLS	$BR_m \cdot [D_{2000}^{2004} + D_{2010}^{2004}]$	-0.365	-0.204	-0.126	-0.188	-0.371	-0.234	-0.0388	-0.254
		[0.576]	[0.397]	[0.216]	[0.229]	[0.528]	[0.368]	[0.168]	[0.216]
		(5.551)	(7.045)	(6.574)	(7.059)	(5.090)	(7.033)	(5.666)	(7.033)
2SLS	$BR_m \cdot D_{2000}^{2010}$	-0.344	-0.180	-0.0447	-0.117	-0.274	-0.135	0.106	-0.0829
		[0.555]	[0.403]	[0.231]	[0.241]	[0.490]	[0.365]	[0.196]	[0.221]
		(10.59)	(13.14)	(13.23)	(13.17)	(10.05)	(13.27)	(10.01)	(13.27)
Observations		12,659	12,653	12,628	12,634	948	945	945	945
		B. Dependent variable: Average log hourly wages of earlier immigrants							
OLS		0.0353	0.0191	-0.00149	-0.00106	0.295	0.250	0.115	0.0934
		[0.0605]	[0.0616]	[0.0263]	[0.0263]	[0.0787]***	[0.0814]***	[0.0503]**	[0.0494]*
2SLS	$BR_m \cdot [D_{2000}^{2004} + D_{2010}^{2004}]$	0.350	0.365	-0.0729	-0.0902	0.322	0.292	-0.0766	-0.124
		[0.287]	[0.289]	[0.271]	[0.268]	[0.271]	[0.280]	[0.282]	[0.247]
		(4.892)	(5.804)	(5.197)	(5.793)	(3.923v	(5.268)	(4.413)	(5.268)
2SLS	$BR_m \cdot D_{2000}^{2010}$	0.327	0.354	-0.0927	-0.0927	0.353	0.345	-0.144	-0.114
		[0.337]	[0.325]	[0.279]	[0.273]	[0.329]	[0.328]	[0.311]	[0.281]
		(9.407)	(11.34)	(10.27)	(11.29)	(7.844)	(10.54)	(8.942)	(10.54)
Observations		12,796	12,790	12,541	12,629	948	945	945	945
Year/Area fixed effects		√	√	√	√	√	√	√	√
Bartik			√	√	√		√	√	√
Demo. controls				√	Adj. $y_{m,t}$			√	Adj. $y_{m,t}$

Notes: ***, **, *, denote statistical significance at the 1%, 5% and 10% level, respectively. Robust standard errors, clustered by Canton, are given in parentheses. Each row reports the coefficient of a regression of the average log hourly wage in a location and year on the share of new immigrants, $(IM_{m,t}/TOTEMP_{m,t})$, on the total workforce. Row 1 in each panel shows OLS estimates. In row 2 the share of new immigrants is instrumented with two separate dummies for the Phase 1 and Phase 2 of the reform, $BR_m \times D_{2000}^{2004}$ and $BR_m \times D_{2004}^{2010}$. In row 3, the new immigrant share is instrumented with only 1 interaction term for both Phase 1 and Phase 2, $BR_m \times D_{2000}^{2010}$. F-statistics of the first stage is given below the standard errors of each regression in round brackets. Regressions are weighted using the total workforce of cells.

Displacement of Natives and Earlier Immigrants

The insignificant effects of immigrants on native wages found in the previous section confirm previous findings for other countries (e.g. Card (2001), for the US, Glitz (2012) for Germany). It is important, however, to analyze also whether immigration reduced employment of natives. Some studies (e.g. Borjas (2003)) have pointed out that insignificant local effect on wages may still co-exist with important displacement effects of immigrants. If that is the case one should find a negative impact of immigrants on native employment.

To this extent we run a regression like equation (2.6) with the logarithm of total hours worked (in full time equivalents) in area m in year t by group G as the dependent variable. This outcome captures the local, group specific labor supply and any change associated to fewer hours worked (intensive margin) or individual displacement into non-employment (extensive margin) would be measured by this outcome. In this case, the estimates of β_1^G and β_2^G measure whether the total local labor supply of a group, $G \in \{\text{natives, earlier immigrants}\}$, changed differentially in the border region during the opening policy compared to the non-border region. Table 2.4 reports these estimates for natives (Panel A) and earlier immigrants (Panel B). Columns 1 presents estimates using year and area fixed effects only. In addition, column 2 includes the employment Bartik and column 3 also includes average demographic characteristics of an area.[39] Column 4 to 6 repeat the same specifications on level of commuting zones. In the case of natives, the point estimates for both periods, β_1^G and β_2^G, are negative but they are small and never significantly different from zero. Just as for average wages, the total native labor supply did not change differentially in during the period of the differential BR-NBR policy. However, for earlier immigrants and considering commuting zones as units, the coefficients , β_1^G and β_2^G are estimated to be negative and statistically different from zero. As emphasized in other studies for other countries (e.g. D'Amuri et al. (2010)) earlier natives could be more affected by competition of new immigrants than natives, hence the (small) displacement suffered by them

[39]Note that 'adjusting' an outcome measure from individual demographic characteristics like in the case of mean hourly wages is not feasible for total employment. This is why we use local averages of demographic characteristics only as controls.

Table 2.4: Difference-in-Difference Analysis of the Effect of the Opening on Log Total Hours of Natives and Earlier Immigrants

Area level	Municipality			Commuting zone		
	(1)	(2)	(3)	(4)	(5)	(6)
A. Dependent variable: Log total hours worked of natives						
$BR_m \times D_{2000}^{2004}$	-0.0257	-0.0266	-0.0265	-0.0315	-0.0351	-0.0290
	[0.0251]	[0.0244]	[0.0267]	[0.0266]	[0.0256]	[0.0273]
$BR_m \times D_{2004}^{2010}$	-0.00559	-0.00682	-0.00944	-0.0236	-0.0285	-0.0339
	[0.0328]	[0.0305]	[0.0293]	[0.0278]	[0.0248]	[0.0314]
Observations	17,674	17,664	17,489	949	945	945
R-squared	0.972	0.972	0.973	0.988	0.988	0.988
B. Dependent variable: Log total hours worked of earlier immigrants						
$BR_m \times D_{2000}^{2004}$	-0.00512	-0.00563	-0.000266	-0.0666	-0.0718	-0.0723
	[0.0309]	[0.0309]	[0.0390]	[0.0351]*	[0.0318]**	[0.0276]**
$BR_m \times D_{2004}^{2010}$	0.00732	0.00674	0.0150	-0.0624	-0.0683	-0.0625
	[0.0595]	[0.0581]	[0.0589]	[0.0593]	[0.0557]	[0.0519]
Observations	12,801	12,795	12,546	948	945	945
R-squared	0.949	0.949	0.952	0.971	0.971	0.973
Year/Area fixed effects	√	√	√	√	√	√
Bartik		√	√		√	√
Demo. controls			√			√

Notes: ***, **, *, denote statistical significance at the 1%, 5% and 10% level, respectively. Robust standard errors, clustered by Canton, are given in parentheses. BR_m is one for municipalities (commuting zones) in the border region. D_{2000}^{2004} and D_{2004}^{2010} are dummies for the differential opening in *Phase 1*, from 1999 to 2004, and *Phase 2*, from 2004 to 2010, respectively. Regressions are weighted using the total workforce of cells.

To get estimates of the displacement effects that are more comparable to the existing literature, we can use the specification suggested by Peri and Sparber (2011a) instrumenting the change in immigrants with the policy dummies:

$$\frac{\Delta_t^{t+2} E_m^G}{TOTEMP_{m,t}} = \alpha_m + \alpha_t + \delta^G \left(\frac{\Delta_t^{t+2} IM_m}{TOTEMP_{m,t}} \right) + X'_{m,t}\pi + \eta_{m,t} \tag{2.8}$$

where $\frac{\Delta_t^{t+2} E_m^G}{TOTEMP_{m,t}}$ is the change in employment of natives or earlier immigrants between year t and $t+2$ in area m standardised by the area's initial total employment and $\frac{\Delta_t^{t+2} IM_m}{TOTEMP_{m,t}}$ represents the change in the number of immigrants in area m between two subsequent years, standardised by the total labor force in area m at the beginning of the period. Even in this case, equation (2.4) represents the first stage of a 2SLS estimation of immigrant inflow on native displacement.[40]

Appendix table A.9 presents estimates of equation (2.8) for natives (Panel A) and

[40]To account for industry-driven employment growth across local labor markets we use the growth

earlier immigrants (Panel B). Column 1 (column 2) use year fixed effects and fixed effects for municipalities (commuting zones), respectively. Columns 2 (column 5) use the Bartik employment growth measure and Column 3 and (column 6) use additional mean area demographic characteristics as controls. The first row in each panel shows estimates using OLS, while the second and third row present 2SLS estimates using either two interaction terms, $BR_m \times D_{1998}^{2004}$ and $BR_m \times D_{2004}^{2010}$, as instruments for $\frac{\Delta_t^{t+2} IM_m}{TOTEMP_{m,t}}$, or one for the entire period, $BR_m \times D_{1998}^{2010}$. Although OLS coefficients are generally positive and significant, IV estimates are mostly lower (with negative point estimates) and not significantly different from zero. This highlights again the issue that OLS estimates are potentially upward biased. We need to acknowledge, however, that standard errors of the IV estimates are quite large and the F-statistics, which are reported below the standard errors, show that there is little power in the first stage. The low power of the first stage originates from the lower power of the reform in predicting differential growth of newly arriving immigrants across regions in contrast to predicting the differential evolution of immigrant exposure. This is why we take more confidence in the estimates of the direct reform effect in levels presented in table 2.4.

Additionally, we also checked whether the differential opening affects the population dynamics differentially across regions by estimating equation (2.6) for total local population.[41] Appendix table A.10 establishes that population trends are not different in the border region during the time of the differential labor market openness.

Overall, our difference in difference approach confirms no effect of free labor mobility on the wages of average native workers. This confirms large part of the existing literature (e.g. Basten and Siegenthaler (2013) or Favre (2011)) but is based on a much more careful and policy-based identification strategy.. In the case of earlier immigrants, we do find some hints of displacement in the difference-in-difference analysis, but we do not find similar effects for natives. This is consistent with the notion that immigrants are not mainly competitors with natives in the labor market.[42]

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version of the Bartik measure:

$$\left(\frac{\widetilde{\Delta_t^{t+2} E_m^G}}{TOTEMP_{m,t}}\right) = \sum_{i \in \{1,50\}} \left(s_{i,m,1990} \times \frac{\Delta_t^{t+2} E_{-m,i}^G}{TOTEMP_{-m,i,t}}\right)$$

where $s_{m,i,1990}$ is the share of (2-digit) industry $i \in \{1{,}50\}$ on total employment in location m in 1990. $\frac{\Delta_t^{t+2} E_{-m,i,t}^G}{TOTEMP_{-m,i,t}}$ is change in employment of group G in industry i at the national level (excluding region m) between t and $t+2$ divided by industry total employment in year t.

[41] Note that this is the total local residency population, taken from the OFS, which consists of all nationality groups, i.e. natives, earlier immigrants and newly arriving immigrants.

[42] This finding is in line with Favre et al. (2013) who could not establish strong displacement of natives either or Basten and Siegenthaler (2013) who even find that immigrants reduce native unemployment.

2.7 Extensions and Heterogeneity

While the previous section finds no evidence of significant effect of immigration on native wages and employment in aggregate, different degree of complementarity and competition of immigrants with different parts of the native population could produce differential effects across them. We first analyze outcomes on native subgroups and then we analyze the impact on specialization and jobs task content.

2.7.1 Heterogeneity Across Education Groups

In a first step, we investigate whether there is some important heterogeneity in how workers with different educational backgrounds have been affected by the differential labor market opening and its effect on immigrant exposure. Section 2.4.2 established that there was strong educational upgrading among newly arriving immigrants with the share of tertiary educated workers increasing by 14 percentage points between 1998 and 2010 while the share of middle educated only increased by a small amount (3 percentage points) and the share of low educated decreased.[43]

Impact on Wages Across Education Groups

Appendix table A.11 shows separate estimates of equation (2.6) when the dependent variable is the average log hourly wage of highly educated natives (Panel A), middle educated natives (Panel B) or low educated native workers (Panel C). Estimates for education groups of earlier immigrants are reported in appendix table A.12. These tables are similarly structured as previous wage regression tables (e.g. table 2.2).[44] The reported coefficients indicate whether the log hourly wages of a particular group changed differentially in the border region during the time of the differential opening. Estimates in the table for natives indicate that the wages of highly educated natives increased more in the BR but the effect is only significant in the specification controlling with average demographic characteristics (column 3).[45] The point estimates for middle and low educated natives are mostly negative but not statistically significant. According to the estimates

[43]It is important to bear in mind, however, that the substantial growth in the total number of newly arriving immigrants (increase by factor 1.8) means that the number of new immigrants increased in all education groups with the largest gains by highly educated workers (increase by factor 3.5), followed by middle educated (factor 2) and low educated workers (factor 1.2). In contrast, the number of natives with tertiary, middle or low education grew by a factor of 1.6, 1.2 and 0.9 respectively.

[44]To control for industry driven and education specific demand shocks, we use the education group specific Bartik when indicated.

[45]A test of joint significance, cannot reject the null of both coefficients being jointly zero in all specifications.

for earlier immigrants in table A.12, wages do not show a different evolution in the BR during the opening.

Like for average workers, we can test the causal link between the change in immigrant exposure and the change in the wages of natives and earlier immigrants under the additional assumption of the exclusion restriction. 2SLS estimates for the three different education groups are presented in table 2.5 for natives and appendix table A.13 for earlier immigrants. In each table, Panel A reports estimates for highly educated workers, Panel B for middle educated workers and Panel C for low educated workers. In the first row in each panel, we show the 2SLS estimates using two interaction terms as instruments for Phase 1 and Phase 2 of the reform and in the second row we show the estimates using a single interaction term for the entire 2000 to 2010 period.[46] Both strategies give very similar results. Interestingly, the effect of immigrant exposure is only significantly different from zero and positive for highly educated natives and insignificant for all the other groups. To gauge the quantitative importance of this effect, we can considering that the the border and non-border region experienced an up to 4 percentage points larger increase in the share of newly arriving immigrants by 2010. Using our preferred estimate from column 4 (second row) in table 2.5 this translates into 2.1 percentage points (0.513×0.4) larger increase in the wages of highly educated workers in the border region compared to the non-border region by 2010.

[46]We omit OLS estimates for the sake of brevity.

Table 2.5: 2SLS Estimates of the Effect of New Immigrants on Average Log Hourly Wages of Natives, by Education Group

Area level	Municipality				Commuting zone			
Instrument	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	A. Dependent variable: Average log hourly wage of highly educated							
$BR_m \cdot [D_{2000}^{2004} + D_{2010}^{2004}]$	0.602	0.666	0.913	0.464	0.448	0.491	0.516	0.211
	[0.274]**	[0.317]**	[0.329]**	[0.226]*	[0.278]	[0.325]	[0.326]	[0.259]
	(12.69)	(12.29)	(10.70)	(12.66)	(6.602)	(7.218)	(4.707)	(7.218)
$BR_m \cdot D_{2000}^{2010}$	0.671	0.721	0.984	0.513	0.616	0.664	0.847	0.346
	[0.342]*	[0.381]*	[0.434]**	[0.291]*	[0.372]	[0.424]	[0.558]	[0.347]
	(14.65)	(14.10)	(16.01)	(14.42)	(12.02)	(12.24)	(8.826)	(12.24)
Observations	11,216	11,213	11,210	11,109	947	945	945	945
	B. Dependent variable: Average log hourly wage of middle educated							
$BR_m \cdot [D_{2000}^{2004} + D_{2010}^{2004}]$	-0.591	-0.381	-0.299	-0.268	-0.544	-0.411	-0.124	-0.330
	[0.579]	[0.406]	[0.289]	[0.321]	[0.512]	[0.380]	[0.184]	[0.317]
	(5.263)	(4.882)	(4.988)	(4.898)	(4.774)	(4.579)	(4.664)	(4.579)
$BR_m \cdot D_{2000}^{2010}$	-0.573	-0.324	-0.190	-0.145	-0.495	-0.326	0.0268	-0.0972
	[0.533]	[0.379]	[0.269]	[0.312]	[0.470]	[0.349]	[0.238]	[0.286]
	(10.00)	(9.827)	(10.03)	(9.858)	(9.466)	(9.197)	(7.231)	(9.197)
Observations	12,510	12,504	12,490	12,470	948	945	945	945
	C. Dependent variable: Average log hourly wage of low educated							
$BR_m \cdot [D_{2000}^{2004} + D_{2010}^{2004}]$	-0.745	-0.725	-0.613	-0.397	-0.612	-0.607	-0.410	-0.429
	[0.632]	[0.555]	[0.513]	[0.522]	[0.544]	[0.486]	[0.390]	[0.464]
	(3.896)	(4.724)	(4.162)	(4.778)	(4.280)	(5.401)	(5.281)	(5.401)
$BR_m \cdot D_{2000}^{2010}$	-0.818	-0.832	-0.673	-0.431	-0.560	-0.571	-0.271	-0.171
	[0.814]	[0.722]	[0.707]	[0.554]	[0.578]	[0.511]	[0.458]	[0.416]
	(6.053)	(7.953)	(7.018)	(8.047)	(8.270)	(10.66)	(8.943)	(10.66)
Observations	11,594	11,591	11,575	11,423	948	945	945	945
Year/Area fixed effects	√	√	√	√	√	√	√	√
Bartik		√	√	√		√	√	√
Demo. controls			√	Adj. $y_{m,t}$			√	Adj. $y_{m,t}$

Notes: ***, **, *, denote statistical significance at the 1%, 5% and 10% level, respectively. Robust standard errors, clustered by Canton, are given in parentheses. Each row reports the coefficient of a regression of the average log hourly wage in an area and year on the share of new immigrants on the total workforce, $(IM_{m,t}/TOTEMP_{m,t})$. In row 1 in each panel the share of new immigrants is instrumented with two separate dummies for the Phase 1 and Phase 2 of the reform, $BR_m \times D_{2000}^{2004}$ and $BR_m \times D_{2004}^{2010}$. In row 2, the new immigrant share is instrumented with only 1 interaction term for both Phase 1 and Phase 2, $BR_m \times D_{2000}^{2010}$. F-statistics of the first stage is given below the standard errors of each regression in round brackets. Regressions are weighted using the total workforce of cells.

This result is interesting and in some respect somewhat surprising. The highly educated immigrants, appear to be more complementary to highly educated natives than to middle and less educated. This could be because they stimulate, as in Lewis (2011) the adoption of capital and technology that is skill-complementary and hence reverse the pure substitution effect. Alternatively it may be because they generate specialization between natives and immigrants within the group of highly educated which enhances their complementarity, as suggested in Peri and Sparber (2011b). We will explore this channel further.

Displacement by Education Groups

We analyze next the effect of immigrants on native employment by education group, using a similar framework. Our analysis follows the same structure used to study the wage effects of new immigrants. Specifically we estimate (2.6) using the logarithm of total hours worked by natives in an education group and area-year cell as dependent variable. Table 2.6 shows the estimates, separating highly educated (Panel A), middle educated (Panel B) and less educated natives (Panel C). As usual different specifications adopt different geographical units (Municipalities in 1-3 and commuting zones in 4-6) and include different controls. The estimates show mostly small and insignificant effects of immigrants on native labor supply. Only few negative significant effects are reported for the middle educated. A similar, but slightly stronger negative effect can be detected in appendix table A.14 for middle educated earlier immigrants, while no significant effects are estimated on other education groups.

We can also estimate the causal effect of immigrant exposure on the displacement of natives and earlier immigrants by running similar regressions like equation (2.8) for the change in employment of different education groups. These results are reported in the appendix table A.15 for natives and appendix table A.16 for earlier immigrants. The results show no significant displacement of native or earlier immigrant workers with middle education but a slight attraction of workers with high education and a small displacement of low educated workers. As in the aggregate case, however, the 2SLS coefficients are estimated very imprecisely estimated due to the low power in the first stage for immigrant growth which is why we need interpret these results with some caution.

It is interesting to notice that, vis-a-vis positive wage effects for highly educated natives, new immigrants do not have any impact on employment of that group. Instead, if one has to identify the group less positively affected, with potential mild displacement, the group of middle educated seem to be such a group. The positive effect on highly educated can stem from different occupational specialization of immigrants and from induced upgrade and specialization of highly educated natives. To the contrary the middle educated may have less scope for such upgrade and specialization and may have not enjoyed such benefits.

Table 2.6: Difference-in-Difference Analysis of the Effect of the Opening on Log Total Hours of Natives, by Education Group

Area level	Municipality			Commuting zone		
	(1)	(2)	(3)	(4)	(5)	(6)
A. Dependent variable: Log total hours of highly educated						
$BR_m \times D_{2000}^{2004}$	-0.0128	-0.0129	-0.0248	-0.0329	-0.0317	-0.0510
	[0.0541]	[0.0543]	[0.0399]	[0.0636]	[0.0634]	[0.0322]
$BR_m \times D_{2004}^{2010}$	0.0312	0.0311	-0.0229	-0.00362	-0.00218	-0.0464
	[0.0567]	[0.0578]	[0.0400]	[0.0541]	[0.0541]	[0.0467]
Observations	13,237	13,233	13,210	948	945	945
R-squared	0.972	0.972	0.981	0.986	0.986	0.992
B. Dependent variable: Log total hours of middle educated						
$BR_m \times D_{2000}^{2004}$	-0.0261	-0.0352	-0.0193	-0.0324	-0.0364	-0.0217
	[0.0226]	[0.0229]	[0.0243]	[0.0297]	[0.0295]	[0.0280]
$BR_m \times D_{2004}^{2010}$	-0.0481	-0.0604	-0.0264	-0.0598	-0.0650	-0.0288
	[0.0258]*	[0.0244]**	[0.0271]	[0.0315]*	[0.0300]**	[0.0325]
Observations	17,007	16,997	16,882	949	945	945
R-squared	0.969	0.969	0.971	0.986	0.986	0.987
C. Dependent variable: Log total hours of low educated						
$BR_m \times D_{2000}^{2004}$	-0.0234	-0.0229	-0.00877	-0.0571	-0.0569	-0.0558
	[0.0699]	[0.0722]	[0.0500]	[0.0696]	[0.0722]	[0.0421]
$BR_m \times D_{2004}^{2010}$	0.110	0.110	0.0482	0.0731	0.0728	-0.0149
	[0.0821]	[0.0803]	[0.0498]	[0.0712]	[0.0679]	[0.0476]
Observations	14,073	14,070	14,016	948	945	945
R-squared	0.913	0.913	0.939	0.942	0.943	0.968
Year/Area fixed effects	√	√	√	√	√	√
Bartik		√	√		√	√
Demo. controls			√			√

Notes: ***, **, *, denote statistical significance at the 1%, 5% and 10% level, respectively. Robust standard errors, clustered by Canton, are given in parentheses. BR_m is one for municipalities (commuting zones) in the border region. D_{2000}^{2004} and D_{2004}^{2010} are dummies for the differential opening in *Phase 1*, from 1999 to 2004, and *Phase 2*, from 2004 to 2010, respectively. Regressions are weighted using the total workforce of cells.

2.7.2 Mobility Across Management Levels and Job Tasks

How is it possible that highly educated natives have gained from the increase in immigrant exposure which was, as documented in section 2.4.2, most pronounced for highly educated workers, while middle educated natives, for whom immigrant exposure increased less, have lost?

One potential channel through which immigrants may help highly educated natives is by encouraging them to move into jobs in which they were more complementary to the newly arriving immigrants (Lewis and Peri, 2014). Previous studies such as Peri and Sparber (2009), D'Amuri and Peri (2014) and Foged and Peri (2013) for instance, pointed out that low-skilled natives, who are particularly exposed to low-educated immigration have moved away from manual intensive occupations to more communication intensive occupations, where they have a comparative advantage, in response to immigration. A similar mechanism may also take place on the other side of the skill spectrum. For the U.S., Peri and Sparber (2011b) show that immigrants with a college degree are particularly concentrated in STEM occupations (science, technology, engineering and math) while natives specialise in supervisory, managerial an interactive type of occupations and move more towards those with increasing immigrant exposure. It is not clear ex-ante whether a similar mechanism of native sorting is induced by immigration in Switzerland as immigrants mostly come from neighbouring countries with potentially a similar language background as the natives in destination where they choose to work.[47] We will analyze this channel.

We can test this hypothesis for the Swiss case by digging a bit deeper into our data. On the one hand, the SESS data contains information on the management level of each worker. We distinguish four categories from *no management position*, over *lower* and *intermediate management* to *higher and highest management*.[48] In addition, there is information on how challenging the requirements of a job are. Here, we distinguish three categories ranging from *simple and repetitive tasks*, *intermediate tasks* and *complex tasks*, which comprise 'highly challenging and difficult tasks'.[49]

First, we investigate whether and how the share of workers in different management

[47] Unsurprisingly, inspecting the data reveals that a large share of each nationality's immigrant group chooses to work in the region where it masters the prevailing language: In 2010, 94% and 95% of resident immigrants from Austria and Germany, respectively, work in the German-speaking area of Switzerland, 78% of immigrants from France work in the French-speaking area whereas Italians are a little bit more evenly distributed: 38% work in the Italian-speaking part of Switzerland and 40% and 20% in the German- and French-speaking part, respectively. This pattern is even more pronounced among cross-border workers, see appendix table A.4.

[48] We collapse the categories '*lowest management*' and '*lower management*' to form one single category.

[49] The intermediate category is a combination of two categories '*job requiring occupational knowledge*' and '*job requiring autonomous & qualified working*'.

positions changes for a given education group. If highly educated natives, for instance, responded to rising immigrant exposure by climbing up the hierarchy ladder, we would expect that the share of workers in high management positions increases among highly educated natives at the expense of lower hierarchy positions. To analyse this casual channel, we use a 2SLS estimation of the form of equation (2.7) and regress the share of an education group's workers belonging to a certain management level on immigrant exposure instrumented with our strongest instrument, $BR_m \times D^{2010}_{2000}$. We run separate regressions for each of the four management level groups (no management position, low, intermediate and high positions). Table 2.7 present these estimates for natives. Each entry in this table represents a separate regression; Columns 1 to 4 (columns 5 to 8) use specifications with different sets controls, on the municipality (commuting zone) level, as in earlier tables. The first line in Panel A of table 2.7 shows the effect of immigrant exposure on the share of workers in high management positions among highly educated natives. The second, third and fourth line repeat the same exercise for the groups with intermediate, low or no management positions, respectively.[50]

The results indicate that a one percentage point increase in the employment share of new immigrants produced a 0.7 to 1.2 percentage point increase in the share of workers in high management positions among highly educated natives. This is a sizeable effect suggesting that the up to 4 percentage points higher immigrant exposure in the border region lead to an up to 4.8 percentage point larger share of workers in high management positions among the high educated. As the average share of highly educated in top management jobs was 22% in 1998 (these average shares are reported in the first column of the table under the group name), new immigrants have increased the top management group of highly educated natives by more than 20% of its size relative to the other groups. There are no significant effects on the intermediate hierarchy groups, and the point estimates suggest that the gain in the top management group come at the expenses of shrinking the lower hierarchy groups.

Panel B indicates that for middle educated natives there was not an equally strong push towards managerial upgrade. While it appears that immigration pushed some middle educated natives out of the "no-management" occupations, and there are some gains among the low or intermediate management positions these effects are not significant, and no effect on the top management group is detectable. Finally among less educated natives (Panel C), there is some evidence that upward pressure into intermediate management positions might have come from immigrants. However the number of less educated in these jobs is so small that overall this might have been a negligible effect. In the case of earlier

[50]Note that the coefficients across hierarchy groups add up to zero as these are mutually exclusive and exhaustive groups.

immigrants, the point estimates are to some degree smaller, but otherwise qualitatively very similar to those of natives but most coefficients are not different from zero. These estimates are reported in appendix table A.17 for completeness.

Table 2.7: 2SLS Estimates of the Effect of New Immigrants on the Distribution of Native Workers Across Different Management Levels within Education Groups

Area level	Municipality				Commuting zone			
Dependent variable (Group Share in 1998)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				A. Highly educated				
Share in high manag.	0.673	0.656	0.962	0.777	0.757	0.748	1.264	0.817
(0.222)	[0.265]**	[0.268]**	[0.331]***	[0.288]**	[0.345]**	[0.354]**	[0.549]**	[0.330]**
Share in middle manag.	-0.174	-0.196	-0.336	-0.290	-0.191	-0.220	-0.768	-0.313
(0.229)	[0.348]	[0.351]	[0.397]	[0.360]	[0.375]	[0.379]	[0.470]	[0.400]
Share in low manag.	0.242	0.253	0.210	0.00451	0.217	0.229	0.391	0.0606
(0.289)	[0.654]	[0.658]	[0.716]	[0.663]	[0.707]	[0.718]	[0.827]	[0.720]
Share in no manag.	-0.741	-0.713	-0.837	-0.491	-0.783	-0.757	-0.887	-0.564
(0.259)	[0.531]	[0.571]	[0.595]	[0.578]	[0.557]	[0.599]	[0.894]	[0.594]
Observations	11,202	11,199	11,196	11,064	947	945	945	945
R-squared	0.457	0.460	0.473	0.435	0.608	0.612	0.633	0.516
F-stats	14.54	14.94	17.00	15.28	12.02	12.47	10.22	12.47
				B. Middle educated				
Share in high manag.	-0.0852	-0.0581	-0.0164	-0.0223	-0.0890	-0.0516	0.00583	-0.0243
(0.033)	[0.130]	[0.116]	[0.114]	[0.149]	[0.148]	[0.139]	[0.181]	[0.170]
Share in middle manag.	0.0758	0.131	0.171	0.147	0.0914	0.137	0.320	0.158
(0.06 1)	[0.103]	[0.100]	[0.114]	[0.115]	[0.118]	[0.117]	[0.178]*	[0.123]
Share in low manag.	0.531	0.544	0.518	0.553	0.606	0.646	0.815	0.717
(0.250)	[0.494]	[0.452]	[0.476]	[0.453]	[0.477]	[0.441]	[0.485]	[0.463]
Share in no manag.	-0.521	-0.617	-0.672	-0.677	-0.609	-0.732	-1.140	-0.851
(0.656)	[0.549]	[0.508]	[0.530]	[0.485]	[0.569]	[0.529]	[0.631]*	[0.524]
Observations	12,468	12,462	12,449	12,414	948	945	945	945
R-squared	0.399	0.390	0.390	0.339	0.632	0.620	0.593	0.420
F-stats	10.00	10.91	10.88	10.96	9.466	9.682	7.249	9.682
				C. Low educated				
Share in high manag.	0.0387	0.0386	0.0597	0.177	0.0173	0.0170	0.0544	0.123
(0.006)	[0.0781]	[0.0771]	[0.0846]	[0.0985]*	[0.0734]	[0.0745]	[0.102]	[0.0920]
Share in middle manag.	0.199	0.199	0.209	0.288	0.136	0.136	0.170	0.219
(0.011)	[0.115]*	[0.107]*	[0.137]	[0.165]*	[0.0777]*	[0.0763]*	[0.0975]*	[0.118]*
Share in low manag.	0.297	0.297	0.267	0.0708	0.306	0.305	0.289	0.0889
(0.103)	[0.511]	[0.530]	[0.608]	[0.575]	[0.518]	[0.534]	[0.636]	[0.565]
Share in no manag.	-0.535	-0.535	-0.535	-0.535	-0.460	-0.458	-0.513	-0.431
(0.88)	[0.500]	[0.521]	[0.581]	[0.536]	[0.548]	[0.567]	[0.668]	[0.581]
Observations	11,498	11,495	11,480	11,276	948	945	945	945
R-squared	0.304	0.305	0.305	0.319	0.379	0.382	0.394	0.384
F-stats	6.090	7.974	7.069	8.000	8.270	10.50	8.673	10.50
Year/Area fixed effects	√	√	√	√	√	√	√	√
Bartik		√	√	√		√	√	√
Demo. controls			√	Adj. $y_{m,t}$			√	Adj. $y_{m,t}$

Notes: ***, **, *, denote statistical significance at the 1%, 5% and 10% level, respectively. Robust standard errors, clustered by Canton, are given in parentheses. Each row reports the coefficient of a regression of the share of a management level on the total workforce of an education group in a location and year on the share of new immigrants, $(IM_{m,t}/TOTEMP_{m,t})$, on the total workforce. The new immigrant share is instrumented with only 1 interaction term for both Phase 1 and Phase 2, $BR_m \times D_{2000}^{2010}$. F-statistics of the first stage is the same for each management level among an education group. Regressions are weighted using the total workforce of cells.

We then analyze how immigrant exposure affected the allocation of native and earlier immigrant workers within an education group across different production tasks. In this case the dependent variable is the share of workers in jobs mainly requiring one of the three type of tasks for a given education group of native workers. These estimates are presented in table 2.8 which is organized similarly to the previous table.[51] The estimates in Panel A show that immigrant exposure had no effect on the distribution of tasks among highly educated workers. However, among middle educated workers, shown in Panel B, there are significant effects. These estimates suggest that a one percentage point increase in immigrant exposure reduced the share working on intermediate tasks by 1.2 to 1.7 percentage points and increased the share working on simple and repetitive tasks by a similar amount. Quantitatively, this translates into a 4.8 to 6.8 percentage point loss (gain) in share of workers doing intermediate (routine) tasks among middle educated natives. As only 12% of workers with an middle education workers were employed in these 'routine' tasks in 1998, this is a substantial effect of immigration. For low educated workers (Panel C), results are mostly insignificant.

[51]The results for earlier immigrants are reported in appendix table A.18 for completeness.

Table 2.8: 2SLS Estimates of the Effect of New Immigrants on the Distribution of Native Workers Across Jobs With Different Task Content Within Education Groups

Area level	Municipality				Commuting zone			
Dependent variable (Group Share in 1998)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				A. Highly educated				
Share in complex tasks	-0.670	-0.678	-0.614	-0.718	-0.589	-0.589	-0.422	-0.656
(0.252)	[0.472]	[0.476]	[0.490]	[0.510]	[0.455]	[0.465]	[0.540]	[0.490]
Share in intermed. tasks	0.600	0.609	0.555	0.545	0.521	0.522	0.325	0.478
(0.725)	[0.430]	[0.435]	[0.458]	[0.486]	[0.406]	[0.417]	[0.494]	[0.459]
Share in routine tasks	0.0701	0.0685	0.0592	0.174	0.0685	0.0669	0.0968	0.177
(0.024)	[0.0923]	[0.0923]	[0.0932]	[0.0860]*	[0.0913]	[0.0915]	[0.110]	[0.0940]*
Observations	11,234	11,231	11,228	11,095	947	945	945	945
R-squared	0.341	0.341	0.344	0.266	0.464	0.464	0.462	0.261
F-stats	14.60	15.00	17.07	15.33	12.02	12.47	10.22	12.47
				B. Middle educated				
Share in complex tasks	-0.00699	0.00541	0.0218	0.0253	0.00273	0.0163	0.113	0.0563
(0.026)	[0.119]	[0.108]	[0.112]	[0.160]	[0.120]	[0.114]	[0.153]	[0.165]
Share in intermed. tasks	-1.219	-1.209	-1.366	-1.304	-1.183	-1.183	-1.688	-1.237
(0.852)	[0.462]**	[0.407]***	[0.391]***	[0.387]***	[0.407]***	[0.368]***	[0.437]***	[0.334]***
Share in routine tasks	1.226	1.204	1.345	1.279	1.181	1.167	1.575	1.181
(0.123)	[0.513]**	[0.445]**	[0.419]***	[0.441]***	[0.448]**	[0.395]***	[0.397]***	[0.388]***
Observations	12,508	12,502	12,488	12,453	948	945	945	945
R-squared	0.001	0.014	-0.038	-0.061	0.202	0.211	0.053	0.148
F-stats	10.02	10.92	10.90	10.98	9.466	9.682	7.249	9.682
				C. Low educated				
Share in complex tasks	0.00276	0.00281	0.00285	0.155	-0.00251	-0.00216	0.0215	0.122
(0.005)	[0.0782]	[0.0751]	[0.0827]	[0.0805]*	[0.0700]	[0.0649]	[0.0773]	[0.0761]
Share in intermed. tasks	0.105	0.105	0.112	-0.0549	0.515	0.516	0.605	0.317
(0.297)	[0.714]	[0.707]	[0.795]	[0.663]	[0.661]	[0.665]	[0.856]	[0.680]
Share in routine tasks	-0.108	-0.108	-0.115	-0.101	-0.513	-0.514	-0.626	-0.439
(0.699)	[0.740]	[0.730]	[0.813]	[0.693]	[0.662]	[0.667]	[0.866]	[0.704]
Observations	11,587	11,584	11,568	11,365	948	945	945	945
R-squared	0.388	0.389	0.393	0.379	0.382	0.382	0.387	0.361
F-stats	6.051	7.907	6.998	7.978	8.270	10.50	8.673	10.50
Year/Area fixed effects	√	√	√	√	√	√	√	√
Bartik		√	√	√		√	√	√
Demo. controls			√	Adj. $y_{m,t}$			√	Adj. $y_{m,t}$

Notes: ***, **, *, denote statistical significance at the 1%, 5% and 10% level, respectively. Robust standard errors, clustered by Canton, are given in parentheses. Each row reports the coefficient of a regression of the share of a task group on the total workforce of an education group in a location and year on the share of new immigrants, $(IM_{m,t}/TOTEMP_{m,t})$, on the total workforce. The new immigrant share is instrumented with only 1 interaction term for both Phase 1 and Phase 2, $BR_m \times D^{2010}_{2000}$. F-statistics of the first stage is the same for each task group among an education group. Regressions are weighted using the total workforce of cells.

Overall the results of this subsection suggest that highly educated workers managed to escape competition from similarly educated, new immigrants by climbing up the managerial ladder. In fact the presence of highly educated foreigners, probably skilled but not very well equipped to manage Swiss firms, may have increased the demand for this managerial skills by natives. Highly skilled natives may have been the best positioned to supply these important, highly paid and immigrant-complementary skills. Hence their positive wage effect with no displacement. At the other hand of the spectrum the less educated were not affected much in terms of competition or complementarity by skilled immigrants and neither changed their specialization much nor they had significant wage and employment effect. Among natives and earlier immigrants with middle education, finally, we may find the group that benefitted the least and possibly lost to some degree from immigrants competition. As their skills might be in part replaced by new immigrants and as they did not upgrade their management position, this group is the one that did not gain in terms of wage and might have experienced some displacement.

2.8 Conclusion

What is the effect of abolishing immigration restrictions on the inflow of immigrants and what are the consequences for natives in the labor market? Although these are popular questions among practitioners and policy makers, there is remarkably little guidance in the economic literature on what the answers to these questions could be.

In this paper, we exploit the case of Switzerland's integration into the European labor market after 1999, which accidentally created the perfect environment to study the causal effect of removing immigration restriction using a difference-in-difference design. The Swiss case features two different parts of the country experiencing different timing in the implementation of the free movement policy for EU workers between 1999 and 2007. In particular between 2004 and 2007 we have two parts of the country, that suddenly found themselves under very different immigration regimes for a group of workers. Access to labor markets by cross-border workers (CBW), which are foreign workers commuting to work from a neighboring country (Italy, France, Germany or Austria) were fully liberalized in the Swiss border region as of 2004, while they were still forbidden in the rest of the country until 2007. This created a time window between 2004 and 2007 in which the border region were essentially open to immigrants from EU, while non-border region was not.

We leverage this differential degree of openness of the border region relative to the non-border region to analyze the effect of the policy changes on the inflow of new immigrants in a difference-in-difference framework. This analysis reveals that the opening of the border caused an increase of new immigrants by 3 to 4 percentage points of employment. Most of the differential increase in share of new immigrants took place after 2004, when the BR fully liberalized, but the difference persisted rafter 2007, when immigration restrictions were abolished for all EU immigrants (CBW and RI) in both regions. Our results suggest that this persistence may be due to the ‘‘first mover advantage’’ of the border region that may have generated some inertia.

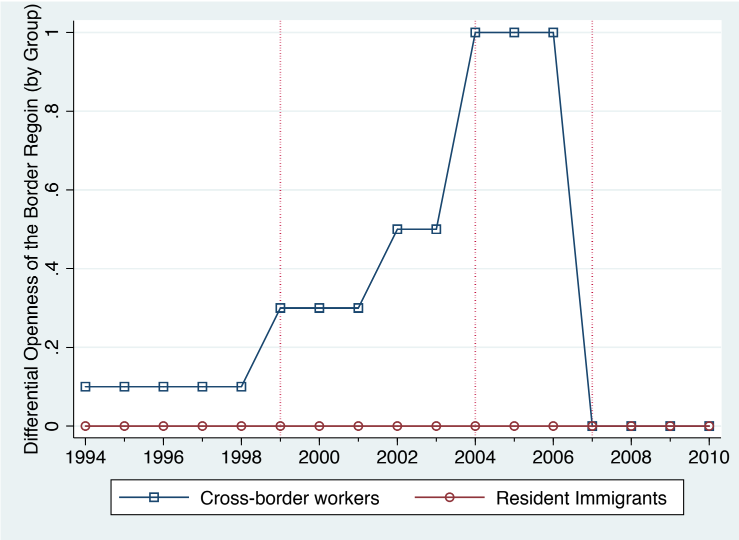
We exploit the same differential policy treatment of the border and non-border region to analyze the consequences for natives and earlier immigrant workers in the labor market. These results suggest that average wages of both groups were not negatively affected from the opening policy and the induced inflow of new immigrants. In addition, we do not find evidence of displacement of average native workers. There is some evidence that earlier immigrants might have suffered some displacement on average. When we analyze these affects by education groups, we find evidence that highly educated natives benefited from immigration in terms of higher wages while middle educated natives and earlier immigrants, may have experienced mild displacement while less educated were unaffected. A subsequent analysis on the management level and the task content of native workers shows that the immigration inflow pushed a larger share of highly educated natives to work in top management positions, as they may have created demand and complementarity for such roles. This helps to explain, why this group of workers benefited the most from the inflow of immigrants. On the other hand, we find evidence that a larger share of middle educated natives was induced to leave jobs requiring professional know-how and work instead in jobs with simple and repetitive task requirements. This may be responsible for the mild displacement suffered by this group.

While the effect of immigration on the beneficial resorting of highly educated natives has also been documented in the academic literature, there is less comparable evidence for the negative effect we find on middle educated natives in terms of displacement and resorting into less attractive jobs. The reason for this might be that the lions share of new immigrant in Switzerland speak one of the country's three dominant languages and sort overwhelmingly into areas where they can use this skill. This increases their similarity with native workers.

2.A Appendix

2.A.1 Figures

Figure A.1: Schematic Illustration of the Relative Openness of the Border Region to Immigration from Different Immigrant Groups



Notes: 0 indicates similar openness of the border and non-border to a particular group of immigrants, 1 indicates maximal differential openness (subjective metric for illustrational purpose). The increase in openness of the border region for cross-border workers is indicated as smaller steps (subjective metric), whereas the implementation of the free movement policy for cross-border workers in 2004 is indicated as maximal difference in openness. Dotted horizontal lines indicate the announcement of the policy in 1999 and the important legislation changes in 2004 and 2007.

Figure A.2: Evolution of the Biannual Change in the Number of New Immigrants Per Total Initial Employment (Left Panel) and Its Difference Between the Border and the Non-Border Region (Right Panel)

Notes: The left figure plots the change in the number of newly arriving immigrants in each region between two subsequent years, $\Delta_t^{t+2} IM_m$, per total initial local employment, $TOTEMP_{m,t}$. The right figure plots the difference in this growth measure between both regions for each two-year period. Vertical lines indicate June 21 1999, when the agreement was signed, June 1 2004, when the labor markets of the border region and the non-border were liberalised differentially, and and June 1 in 2007, when the differential openness of the border region ended. Note that years indicate the labor market situation by October 31 of the corresponding wave. SESS data.

Figure A.3: Plot of Coefficients and 5%-Confidence Interval of the Year Analysis of the Evolution of the Biannual Change in the Number of New Immigrants Per Total Initial Employment (Equation (2.5), Base Period = 1996 to 1998)

Notes: The figure plots coefficients (straight line) and the 5%-confidence interval (dashed line) of an estimate of equation (2.5) including municipality and year fixed effects, shown in column 3 of table A.7. Vertical lines indicate June 21 1999, when the agreement was signed, June 1 2004, when the labor markets of the border region and the non-border were liberalised differentially, and June 1 in 2007, when the differential openness of the border region ended. Note that years indicate the labor market situation by October 31 of the corresponding wave.

2.A.2 Tables

Table A.1: Characteristics of Natives and New Immigrants, 1998 and 2010

	Natives			New immigrants		
	1998	2010	Change	1998	2010	Change
Demographic characteristics						
Share highly educated	0.189	0.248	0.059	0.159	0.300	0.141
Share middle educated	0.670	0.646	-0.024	0.379	0.406	0.027
Share low educated	0.141	0.106	-0.035	0.462	0.294	-0.167
Mean age	39.505	41.097	1.591	36.568	37.753	1.185
Mean tenure	8.291	8.199	-0.092	5.754	4.852	-0.902
Share male	0.598	0.543	-0.055	0.679	0.630	-0.048
Mean log hourly real wage	3.543	3.581	0.038	3.368	3.507	0.139
Mean full time equivalent	0.877	0.826	-0.051	0.945	0.911	-0.035
Total number of workers	1,431,409	1,780,690	349,281	212,366	390,216	177,850
Sample observations	248,037	823,306	575,269	33,211	182,983	149,772
Occupation shares (ranked by mean wage in 1998)						
Management	0.034	0.034	0.000	0.015	0.021	0.006
Evaluation/Consultancy/Certification	0.051	0.064	**0.014**	0.019	0.050	**0.031**
Analysis/Programming/Operating	0.027	0.032	0.004	0.028	0.041	**0.013**
R&D	0.016	0.017	0.001	0.030	0.040	**0.010**
Education	0.021	0.029	**0.007**	0.009	0.019	0.009
Trade	0.020	0.019	-0.001	0.007	0.012	0.005
Logistics	0.024	0.023	-0.001	0.015	0.020	0.005
Planning/Design	0.043	0.038	**-0.005**	0.022	0.033	**0.011**
Accounting/HR	0.058	0.056	-0.002	0.020	0.030	0.010
Culture/Information/Recreation	0.011	0.020	**0.009**	0.005	0.012	0.007
OtherAdmin	**0.083**	**0.073**	**-0.009**	0.036	0.052	**0.015**
Security	0.004	0.010	0.006	0.002	0.004	0.002
Machinery	0.065	0.061	-0.004	0.047	**0.055**	0.008
Administration/Clerks	**0.078**	0.054	**-0.024**	0.019	0.024	0.005
Construction	**0.075**	**0.067**	**-0.008**	**0.155**	**0.117**	**-0.038**
Medical/Nursing	0.056	**0.084**	0.028	0.043	0.051	0.008
Transport	0.046	0.042	-0.003	**0.053**	0.037	**-0.016**
Manufacturing/Processing	**0.125**	**0.095**	**-0.031**	**0.237**	**0.152**	**-0.086**
Restoration/Craft	0.002	0.001	0.000	0.001	0.002	0.002
Retail	**0.098**	**0.099**	0.001	**0.049**	**0.055**	0.006
Cleaning	0.012	0.021	**0.009**	0.020	0.047	**0.027**
Hotel/Catering	0.048	0.055	**0.007**	**0.160**	**0.120**	**-0.040**
Body/Textile Services	0.005	0.007	0.002	0.008	0.007	**-0.002**
1-digit industry shares						
Agriculture/Fishing/Mining	0.004	0.007	0.003	0.005	0.007	0.002
Manufacturing	0.262	0.209	**-0.053**	0.337	0.266	**-0.070**
Utilities	0.007	0.008	0.001	0.001	0.002	0.001
Construction	0.079	0.075	-0.004	0.151	0.113	**-0.038**
Wholesale/Retail/Repair	0.212	0.204	-0.008	0.125	0.143	0.018
Hotels/Restaurants	0.044	0.047	0.003	0.157	0.116	-0.041
Transport/Communication/Storage	0.063	0.047	-0.015	0.048	0.042	-0.006
Financial Intermediation	0.095	0.074	-0.021	0.026	0.034	0.008
Real Estate/R&D/IT/Business activities	0.105	0.137	**0.032**	0.062	0.160	**0.098**
Admin/Education/Health	0.100	0.150	**0.049**	0.065	0.086	**0.021**
Personal Services	0.029	0.042	0.013	0.022	0.030	0.008

Notes: Occupations are ranked by the main log hourly wage in 1998. Occupations with the top 5 largest shares by year and nationality and the top 5 and bottom 5 gains and losses by nationality are marked bold. See definitions in section 2.4. SESS data.

Table A.2: Regional Characteristics in 1998

	Border region	Non-border region
Demographics characteristics		
Share highly educated	0.178	0.150
Share middle educated	0.585	0.616
Share low educated	0.237	0.234
Mean age	39.4	38.7
Mean tenure	8.017	8.085
Share male	0.618	0.608
Mean log hourly wage	3.515	3.454
Mean full time equivalent	0.896	0.873
1-digit industry shares		
Agriculture/Fishing/Mining	0.004	0.003
Manufacturing	0.292	0.258
Utilities	0.005	0.005
Construction	0.089	0.123
Wholesale/Retail/Repair	0.185	0.224
Hotels/Restaurants	0.055	0.081
Transport/Communication/Storage	0.055	0.056
Financial Intermediation	0.087	0.058
Real Estate/R&D/IT/Business activities	0.102	0.077
Admin/Education/Health	0.096	0.087
Personal Services	0.029	0.027
Geography		
Share urban	0.867	0.732
# Cities with population $\geq$ 50k	7	2
Share mountainous	0.248	0.430
Mean driving time (min) to border crossing	29.3	62.8
Share German speaking	0.679	0.898
Share French speaking	0.263	0.090
Share Italian/Romansh speaking	0.058	0.011
Mean municipality size (workforce)	1214	852
Nr workers	1,463,422	497,469
Nr observations	249,155	83,106

Notes: See definitions in section 2.4 for demographic characteristics and industry shares of SESS data in 1998. Distance data are taken from search.ch map data. Geography characteristics are taken from Schuler et al. (2005) using the municipality code of each observation in the SESS data.

Table A.3: Characteristics of Cross-Border Workers and Resident Immigrants in the Border Region in 1998 and 2010

	Cross-border workers			Resident immigrants		
	1998	2010	Change	1998	2010	Change
Demographic characteristics						
Share highly educated	0.153	0.279	0.126	0.185	0.337	0.152
Share middle educated	0.513	0.490	-0.024	0.253	0.317	0.064
Share low educated	0.334	0.232	-0.102	0.562	0.346	-0.216
Mean age	39.660	40.457	0.797	33.722	35.424	1.702
Mean tenure	8.670	7.213	-1.457	2.879	2.906	0.026
Share male	0.693	0.660	-0.033	0.665	0.598	-0.067
Mean log hourly real wage	3.455	3.536	0.081	3.305	3.491	0.186
Mean full time equivalent	0.956	0.936	-0.020	0.933	0.885	-0.048
Total number of workers	103,863	175,206	71,343	81,050	167,021	85,971
Origin country shares						
Austria	0.051	0.030	-0.021	0.032	0.026	-0.006
France	0.504	0.494	-0.010	0.138	0.115	-0.023
Italy	0.226	0.237	0.011	0.092	0.087	-0.006
Germany	0.209	0.209	0.000	0.252	0.356	0.104
Share on total immigrant group	0.990	0.970		0.514	0.584	

Notes: Demographic characteristics are calculated using SESS data. The origin country shares of the four neighbouring countries were calculated using the national Census in 2000 and 2010 to 2012 in the case of RI and using data on CBW from the FSO in 1998 and 2010 (the official name for this dataset is "Grenzgängerstatistik"). Note that an 'origin country' is the nationality of a worker in the CBW data whereas it is the country of birth in the Census. Furthermore, in the Census new resident immigrants are defined as individuals having not lived in Switzerland 5 years ago as in Beerli and Indergand (2014).

Table A.4: Distribution of Cross-Border Workers and Resident Immigrants Across Language Regions in 2010

	Language region				Immigrant group
	German	French	Italian	Romansh	share
Resident Immigrants					
Germany	0.954	0.034	0.006	0.007	0.367
Portugal	0.391	0.566	0.026	0.017	0.130
France	0.210	0.782	0.008	0.000	0.106
Italy	0.399	0.216	0.379	0.005	0.078
Ex-Jugoslavia	0.799	0.163	0.036	0.003	0.053
Austria	0.936	0.054	0.010	0.000	0.027
Cross-Border Workers					
France	0.246	0.753	0.001	0.000	0.494
Italy	0.083	0.018	0.891	0.008	0.237
Germany	0.983	0.012	0.004	0.000	0.209
Austria	0.973	0.008	0.002	0.017	0.030
United Kingdom	0.339	0.633	0.028	0.000	0.007

Notes: The origin country shares of the four neighbouring countries are calculated using the national Census in 2000 and 2010 to 2012 in the case of RI and data on CBW from the FSO in 1998 and 2010 (the official name for this dataset is "Grenzgängerstatistik"). Note that an 'origin country' is the nationality of a worker in the CBW data whereas it is the country of birth in the Census. Furthermore, in the Census new resident immigrants are defined as individuals having not lived in Switzerland 5 years ago as in Beerli and Indergand (2014).

Table A.5: Year Analysis of the Evolution of the Share of New Immigrants on Total Employment

Dependent variable: Share of new immigrants on total employment

Area level	Municipality			Commuting zone		
	(1)	(2)	(3)	(4)	(5)	(6)
$BR_m \times D_{1994}$	-0.00766	-0.00683	-0.00463	-0.00344	-0.00797	-0.00645
	[0.00886]	[0.00819]	[0.00664]	[0.00780]	[0.00782]	[0.00594]
$BR_m \times D_{1996}$	0.00751	0.00432	0.00539	0.00753	0.00394	0.00500
	[0.00496]	[0.00629]	[0.00712]	[0.00546]	[0.00584]	[0.00586]
$BR_m \times D_{2000}$	0.00909	0.00654	0.00987	0.0103	0.00816	0.0112
	[0.00427]**	[0.00452]	[0.00522]*	[0.00331]***	[0.00323]**	[0.00368]***
$BR_m \times D_{2002}$	0.00949	0.00939	0.0129	0.0109	0.00858	0.0116
	[0.00620]	[0.00611]	[0.00644]*	[0.00548]*	[0.00528]	[0.00548]**
$BR_m \times D_{2004}$	0.0159	0.0149	0.0190	0.0180	0.0155	0.0190
	[0.00813]*	[0.00896]	[0.00866]**	[0.00733]**	[0.00812]*	[0.00774]**
$BR_m \times D_{2006}$	0.0234	0.0225	0.0264	0.0248	0.0227	0.0261
	[0.00998]**	[0.0111]*	[0.0105]**	[0.00959]**	[0.0107]**	[0.0102]**
$BR_m \times D_{2008}$	0.0316	0.0281	0.0331	0.0337	0.0293	0.0336
	[0.0110]***	[0.0125]**	[0.0119]***	[0.0108]***	[0.0121]**	[0.0115]***
$BR_m \times D_{2010}$	0.0361	0.0353	0.0387	0.0395	0.0378	0.0408
	[0.0137]**	[0.0151]**	[0.0137]***	[0.0133]***	[0.0146]**	[0.0133]***
BR_m	0.0711			0.0719		
	[0.0282]**			[0.0275]**		
Year fixed effects	√	√	√	√	√	√
Area fixed effects		√	√		√	√
Bartik CZ			√			√
Observations	12,801	12,801	12,795	948	948	945
R-squared	0.118	0.851	0.852	0.164	0.944	0.946

Notes: ***, **, *, denote statistical significance at the 1%, 5% and 10% level, respectively. Robust standard errors, clustered by Canton, are given in parentheses. BR_m is one for municipalities (commuting zones) in the border region. D_t is a dummy for the year t. Regressions are weighted using the total workforce of cells.

Table A.6: Difference-in-Difference Analysis of the Effect of the Opening on New Immigrant Growth (Per Total Initial Employment)

Dependent variable: Growth of new immigrants (per initial total employment)

Area level	Municipality			Commuting zone		
	(1)	(2)	(3)	(4)	(5)	(6)
$BR_m \times D_{1998}^{2004}$	0.00666	0.00715	0.00723	0.00717	0.00739	0.00739
	[0.00534]	[0.00578]	[0.00589]	[0.00607]	[0.00639]	[0.00638]
$BR_m \times D_{2004}^{2010}$	0.0148	0.0147	0.0149	0.0149	0.0150	0.0149
	[0.00590]**	[0.00591]**	[0.00611]**	[0.00635]**	[0.00662]**	[0.00666]**
BR_m	-0.000850			5.40e-05		
	[0.00425]			[0.00435]		
Year fixed effects	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Area fixed effects		$\surd$	$\surd$		$\surd$	$\surd$
Bartik CZ			$\surd$			$\surd$
Observations	9,574	9,574	9,574	842	842	842
R-squared	0.007	0.033	0.033	0.134	0.174	0.174

Notes: ***, **, *, denote statistical significance at the 1%, 5% and 10% level, respectively. Robust standard errors, clustered by Canton, are given in parentheses. BR_m is one for municipalities (commuting zones) in the border region. D_{1998}^{2004} and D_{2004}^{2010} are dummies for the differential opening in *Phase 1*, from 1999 to 2004, and *Phase 2*, from 2004 to 2010, respectively. Regressions are weighted using the total workforce of cells.

Table A.7: Year Analysis of the Evolution of New Immigrant Growth (Per Total Initial Employment)

Dependent variable: Growth of new immigrants (per initial total employment)

Area level	Municipality			Commuting zone		
	(1)	(2)	(3)	(4)	(5)	(6)
$BR_m \times D_{1994}^{1996}$	0.0155	0.0175	0.0174	0.0168	0.0171	0.0172
	[0.0122]	[0.0129]	[0.0128]	[0.0107]	[0.0114]	[0.0115]
$BR_m \times D_{1998}^{2000}$	0.0118	0.0132	0.0132	0.0151	0.0154	0.0154
	[0.00811]	[0.00931]	[0.00917]	[0.00707]**	[0.00777]*	[0.00781]*
$BR_m \times D_{2000}^{2002}$	0.0157	0.0174	0.0173	0.0173	0.0178	0.0179
	[0.0106]	[0.0120]	[0.0120]	[0.0106]	[0.0113]	[0.0113]
$BR_m \times D_{2002}^{2004}$	0.0160	0.0174	0.0175	0.0148	0.0151	0.0151
	[0.00573]**	[0.00625]***	[0.00616]***	[0.00651]**	[0.00691]**	[0.00690]**
$BR_m \times D_{2004}^{2006}$	0.0226	0.0238	0.0239	0.0213	0.0215	0.0214
	[0.00618]***	[0.00684]***	[0.00676]***	[0.00595]***	[0.00634]***	[0.00634]***
$BR_m \times D_{2006}^{2008}$	0.0234	0.0244	0.0245	0.0247	0.0249	0.0249
	[0.00650]***	[0.00703]***	[0.00702]***	[0.00739]***	[0.00783]***	[0.00778]***
$BR_m \times D_{2008}^{2010}$	0.0224	0.0230	0.0231	0.0242	0.0245	0.0244
	[0.00773]***	[0.00850]**	[0.00862]**	[0.00802]***	[0.00841]***	[0.00842]***
BR_m	-0.00879			-0.00847		
	[0.00490]*			[0.00537]		
Year fixed effects	√	√	√	√	√	√
Area fixed effects		√	√		√	√
Bartik CZ			√			√
Observations	9,574	9,574	9,574	842	842	842
R-squared	0.007	0.033	0.033	0.135	0.176	0.176

Notes: ***, **, *, denote statistical significance at the 1%, 5% and 10% level, respectively. Robust standard errors, clustered by Canton, are given in parentheses. BR_m is one for municipalities (commuting zones) in the border region. D_t^{t+2} is a dummy for the period t until $t+2$. Regressions are weighted using the total workforce of cells.

Table A.8: Robustness of Difference-in-Difference Analysis of the Effect of the Opening on the Share of New Immigrants on Total Employment

Dependent variable: Share of new immigrant on total employment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
$BR_m \times D_{2000}^{2004}$	0.0113	0.00626	0.00155	0.00490	0.0126	3.53e-06	0.0144	0.00837	0.00994	0.0232	0.00988	0.0190	-0.0217
	[0.00515]**	[0.00529]	[0.0128]	[0.00546]	[0.00523]**	[0.0117]	[0.0105]	[0.00660]	[0.00384]**	[0.00571]***	[0.00621]	[0.00344]***	[0.00779]**
$BR_m \times D_{2004}^{2010}$	0.0295	0.0204	0.0213	0.0250	0.0322	0.00631	0.0404	0.0201	0.0273	0.0158	0.0149	0.0638	0.0301
	[0.00964]***	[0.00978]**	[0.00757]**	[0.0103]**	[0.00996]***	[0.0148]	[0.0206]*	[0.0109]*	[0.00694]***	[0.0251]	[0.0106]	[0.0135]***	[0.00823]***
Sample BR	all	all	at BRB	w/o top7 cities	urban	rural	BC<20min	BC 20-40min	BC 40-60min	BC>60min	G-speaking	F-speaking	I/R-speaking
Sample NBR	all	all	at BRB	all	urban	rural	all	all	all	all	all	all	all
Year/Area fixed effects	√	√	√	√	√	√	√	√	√	√	√	√	√
Bartik	√		√	√	√	√	√	√	√	√	√	√	√
Industry Trends		√											
Observations	12,795	12,801	2,024	12,722	6,408	6,387	6,444	7,892	5,995	4,176	9,284	6,416	4,903
R-squared	0.852	0.857	0.723	0.837	0.885	0.743	0.876	0.703	0.604	0.607	0.790	0.837	0.879

Notes: ***, **, *, denote statistical significance at the 1%, 5% and 10% level, respectively. Robust standard errors, clustered by Canton, are given in parentheses. BR_m is one for municipalities (commuting zones) in the border region. D_{2000}^{2004} and D_{2004}^{2010} are dummies for the differential opening in *Phase 1*, from 1999 to 2004, and *Phase 2*, from 2004 to 2010, respectively. Regressions are weighted using the total workforce of cells. Distance data are taken from search.ch map data.

Table A.9: OLS and 2SLS Estimates of the Effect of Immigrant Growth on the Change in Hours Worked (Per Initial Total Employment) by Natives and Earlier Immigrants

Area level		Municipality			Commuting zone		
Method	Instrument	(1)	(2)	(3)	(4)	(5)	(6)
A. Dependent variable: Change in hours worked by natives (per initial total employment)							
OLS		1.025	1.025	1.019	1.043	1.042	1.043
		[0.444]**	[0.444]**	[0.442]**	[0.204]***	[0.204]***	[0.199]***
2SLS	$BR_m \cdot [D_{1998}^{2004} + D_{2010}^{2004}]$	0.846	0.869	-0.228	-0.632	-0.912	-0.961
		[2.016]	[2.072]	[1.471]	[1.311]	[1.474]	[1.727]
		(6.487)	(5.696)	(3.934)	(4.902)	(4.472)	(5.174)
2SLS	$BR_m \cdot D_{1998}^{2010}$	-1.390	-1.397	-2.545	-3.927	-4.176	-4.039
		[3.135]	[3.283]	[2.539]	[2.936]	[3.140]	[3.076]
		(4.274)	(4.120)	(4.362)	(3.574)	(3.554)	(5.509)
Observations		9,498	9,498	9,486	842	842	842
B. Dependent variable: Change in hours worked by earlier immigrants (per initial total employment)							
OLS		0.473	0.473	0.446	0.436	0.437	0.428
		[0.0790]***	[0.0790]***	[0.0673]***	[0.0849]***	[0.0847]***	[0.0865]***
2SLS	$BR_m \cdot [D_{1998}^{2004} + D_{2010}^{2004}]$	0.0813	0.180	-0.0670	0.387	0.415	0.522
		[0.862]	[0.813]	[0.887]	[0.730]	[0.713]	[0.603]
		(3.001)	(2.905)	(2.033)	(4.968)	(4.783)	(4.858)
2SLS	$BR_m \cdot D_{1998}^{2010}$	-0.776	-0.680	-0.645	0.400	0.420	0.507
		[2.647]	[2.556]	[2.159]	[1.059]	[1.032]	[0.857]
		(1.191)	(1.143)	(1.350)	(3.413)	(3.526)	(3.805)
Observations		9,574	9,574	9,444	842	842	842
Year/Area fixed effects		√	√	√	√	√	√
Bartik			√	√		√	√
Demo. controls				√			√

Notes: ***, **, *, denote statistical significance at the 1%, 5% and 10% level, respectively. Robust standard errors, clustered by Canton, are given in parentheses. Each row reports the coefficient of a regression of the change in total hours worked by group $G \in \{\text{natives, earlier immigrants}\}$ on total initial employment on the change in the number of new immigrants on the total initial workforce as specified in equation (2.8). Row 1 in each panel shows OLS estimates. In row 2 the growth of new immigrants is instrumented with two separate dummies for the Phase 1 and Phase 2 of the reform, $BR_m \times D_{1998}^{2004}$ and $BR_m \times D_{2004}^{2010}$. In row 3, the new immigrant growth is instrumented with only 1 interaction term for both Phase 1 and Phase 2, $BR_m \times D_{1998}^{2010}$. F-statistics of the first stage is given below the standard errors of each regression in round brackets. Regressions are weighted using the group specific workforce of cells.

Table A.10: Difference-in-Difference Analysis of the Effect of the Opening on Total Population

Dependent variable: Log total population

Area level	Municipality			Commuting zone		
	(1)	(2)	(3)	(4)	(5)	(6)
$BR_m \times D_{2000}^{2004}$	0.00314	0.00387	0.00346	-0.000691	-0.000591	-0.000953
	[0.00920]	[0.00922]	[0.00924]	[0.0105]	[0.0105]	[0.00959]
$BR_m \times D_{2004}^{2010}$	0.0123	0.0127	0.0133	0.00541	0.00550	0.00504
	[0.0203]	[0.0201]	[0.0202]	[0.0227]	[0.0227]	[0.0219]
Year fixed effects	√	√	√	√	√	√
Area fixed effects		√	√		√	√
Bartik CZ			√			√
Observations	21,318	21,291	17,481	954	945	945
R-squared	0.999	0.999	0.999	0.999	0.999	0.999

Notes: ***, **, *, denote statistical significance at the 1%, 5% and 10% level, respectively. Robust standard errors, clustered by Canton, are given in parentheses. BR_m is one for municipalities (commuting zones) in the border region. D_{2000}^{2004} and D_{2004}^{2010} are dummies for the differential opening in *Phase 1*, from 1999 to 2004, and *Phase 2*, from 2004 to 2010, respectively. Regressions are weighted using the total population of cells.

Table A.11: Difference-in-Difference Analysis of the Effect of the Opening on Average Log Hourly Wages of Natives, by Education Group

Area level	Municipality				Commuting zone			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	A. Dependent variable: Average log hourly wage of highly educated							
$BR_m \times D_{2000}^{2004}$	0.0134	0.0134	0.0163	0.00975	0.0143	0.0143	0.0145	0.00934
	[0.0106]	[0.0107]	[0.0120]	[0.00923]	[0.0103]	[0.0103]	[0.00943]	[0.00925]
$BR_m \times D_{2004}^{2010}$	0.0195	0.0186	0.0234	0.0132	0.0161	0.0153	0.0142	0.00728
	[0.0117]	[0.0115]	[0.0112]**	[0.00823]	[0.0120]	[0.0116]	[0.00848]	[0.00897]
Observations	13,197	13,193	13,171	13,013	948	945	945	945
R-squared	0.621	0.621	0.641	0.658	0.835	0.835	0.844	0.868
	B. Dependent variable: Average log hourly wage of middle educated							
$BR_m \times D_{2000}^{2004}$	-0.00418	-0.00396	0.000185	0.00168	-0.00270	-0.00261	0.00184	0.00450
	[0.00530]	[0.00515]	[0.00438]	[0.00567]	[0.00524]	[0.00510]	[0.00491]	[0.00498]
$BR_m \times D_{2004}^{2010}$	-0.0130	-0.0119	-0.00814	-0.00767	-0.0126	-0.0119	-0.00367	-0.00866
	[0.0109]	[0.00984]	[0.00668]	[0.00802]	[0.0101]	[0.00909]	[0.00398]	[0.00761]
Observations	17,000	16,990	16,875	16,858	949	945	945	945
R-squared	0.678	0.678	0.755	0.731	0.883	0.883	0.921	0.918
	C. Dependent variable: Average log hourly wage of low educated							
$BR_m \times D_{2000}^{2004}$	-0.00729	-0.00790	-0.00478	-0.00364	-0.00295	-0.00366	0.00169	0.00749
	[0.0112]	[0.0115]	[0.0126]	[0.00827]	[0.00890]	[0.00924]	[0.0103]	[0.00750]
$BR_m \times D_{2004}^{2010}$	-0.0200	-0.0200	-0.0157	-0.0117	-0.0157	-0.0159	-0.00838	-0.00981
	[0.0132]	[0.0129]	[0.0107]	[0.0127]	[0.0123]	[0.0120]	[0.00831]	[0.0115]
Observations	14,072	14,069	14,015	13,785	948	945	945	945
R-squared	0.508	0.509	0.569	0.547	0.651	0.653	0.694	0.753
Year/Area fixed effects	√	√	√	√	√	√	√	√
Bartik		√	√	√		√	√	√
Demo. controls			√	Adj. $y_{m,t}$			√	Adj. $y_{m,t}$

Notes: ***, **, *, denote statistical significance at the 1%, 5% and 10% level, respectively. Robust standard errors, clustered by Canton, are given in parentheses. BR_m is one for municipalities (commuting zones) in the border region. D_{2000}^{2004} and D_{2004}^{2010} are dummies for the differential opening in *Phase 1*, from 1999 to 2004, and *Phase 2*, from 2004 to 2010, respectively. Regressions are weighted using the group specific workforce of cells.

Table A.12: Difference-in-Difference Analysis of the Effect of the Opening on Average Log Hourly Wages of Earlier Immigrants, by Education Group

Area level	Municipality				Commuting zone			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	A. Dependent variable: Average log hourly wage of highly educated							
$BR_m \times D^{2004}_{2000}$	-0.0383	-0.0385	-0.0413	-0.0182	-0.0313	-0.0312	-0.0332	-0.0129
	[0.0306]	[0.0312]	[0.0312]	[0.0300]	[0.0312]	[0.0317]	[0.0296]	[0.0325]
$BR_m \times D^{2010}_{2004}$	-0.0109	-0.0161	-0.0195	-0.00768	-0.0137	-0.0180	-0.0151	-0.00338
	[0.0273]	[0.0262]	[0.0224]	[0.0240]	[0.0256]	[0.0240]	[0.0220]	[0.0210]
Observations	6,827	6,826	6,786	6,618	903	902	902	901
R-squared	0.606	0.607	0.614	0.587	0.684	0.685	0.692	0.661
	B. Dependent variable: Average log hourly wage of middle educated							
$BR_m \times D^{2004}_{2000}$	-0.00252	-0.00270	-0.00678	-0.00947	-1.76e-05	-0.000288	-0.00944	-0.00390
	[0.0130]	[0.0129]	[0.0108]	[0.0101]	[0.00996]	[0.00995]	[0.00842]	[0.00892]
$BR_m \times D^{2010}_{2004}$	-0.00436	-0.00480	-0.00975	-0.0101	-0.000171	-0.000905	-0.00677	-0.00451
	[0.0109]	[0.0102]	[0.00971]	[0.0102]	[0.00866]	[0.00772]	[0.00771]	[0.00910]
Observations	10,665	10,662	10,547	10,485	945	943	943	943
R-squared	0.493	0.493	0.572	0.550	0.681	0.681	0.733	0.773
	C. Dependent variable: Average log hourly wage of low educated							
$BR_m \times D^{2004}_{2000}$	0.00715	0.00650	0.00236	0.00285	0.00762	0.00672	0.00198	-0.000329
	[0.0103]	[0.00988]	[0.00561]	[0.00497]	[0.00875]	[0.00837]	[0.00488]	[0.00585]
$BR_m \times D^{2010}_{2004}$	-0.00258	-0.00239	-0.00252	-0.00313	-0.000158	-0.000400	-0.000588	-0.00481
	[0.0154]	[0.0149]	[0.0104]	[0.00902]	[0.0146]	[0.0141]	[0.00958]	[0.00765]
Observations	11,034	11,029	10,922	10,892	947	944	944	944
R-squared	0.524	0.524	0.667	0.531	0.583	0.585	0.734	0.674
Year/Area fixed effects	√	√	√	√	√	√	√	√
Bartik		√	√	√		√	√	√
Demo. controls			√	Adj. $y_{m,t}$			√	Adj. $y_{m,t}$

Notes: ***, **, *, denote statistical significance at the 1%, 5% and 10% level, respectively. Robust standard errors, clustered by Canton, are given in parentheses. BR_m is one for municipalities (commuting zones) in the border region. D^{2004}_{2000} and D^{2010}_{2004} are dummies for the differential opening in *Phase 1*, from 1999 to 2004, and *Phase 2*, from 2004 to 2010, respectively. Regressions are weighted using the group specific workforce of cells.

Table A.13: 2SLS Estimates of the Effect of New Immigrants on Average Log Hourly Wages of Earlier Immigrants, by Education Group

Area level	Municipality				Commuting zone			
Instrument	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	A. Dependent variable: Average log hourly wage of highly educated							
$BR_m \cdot \left[D_{2000}^{2004} + D_{2010}^{2004}\right]$	-0.0848	-0.318	-0.430	-0.152	-0.177	-0.404	-0.262	-0.0453
	[0.578]	[0.693]	[0.647]	[0.591]	[0.587]	[0.684]	[0.691]	[0.498]
	(9.877)	(8.307)	(5.650)	(8.148)	(7.082)	(7.239)	(4.601)	(7.233)
$BR_m \cdot D_{2000}^{2010}$	-0.572	-0.785	-0.968	-0.373	-0.616	-0.845	-1.002	-0.260
	[0.867]	[0.979]	[1.009]	[0.833]	[0.925]	[1.032]	[1.186]	[0.858]
	(11.57)	(11.04)	(9.224)	(10.87)	(10.41)	(10.57)	(9.438)	(10.56)
Observations	6,827	6,826	6,786	6,618	903	902	902	901
	A. Dependent variable: Average log hourly wage of middle educated							
$BR_m \cdot \left[D_{2000}^{2004} + D_{2010}^{2004}\right]$	-0.157	0.0509	-0.195	-0.181	-0.00677	0.149	-0.0384	-0.0195
	[0.370]	[0.272]	[0.318]	[0.310]	[0.291]	[0.209]	[0.307]	[0.276]
	(6.397)	(6.556)	(5.586)	(6.534)	(4.389)	(4.597)	(3.187)	(4.597)
$BR_m \cdot D_{2000}^{2010}$	-0.168	0.0848	-0.207	-0.240	-0.00585	0.220	-0.189	-0.0267
	[0.457]	[0.375]	[0.405]	[0.393]	[0.352]	[0.303]	[0.419]	[0.386]
	(11.22)	(13.02)	(11.19)	(12.99)	(8.603)	(9.229)	(6.128)	(9.229)
Observations	10,665	10,662	10,547	10,485	945	943	943	943
	C. Dependent variable: Average log hourly wage of low educated							
$BR_m \cdot \left[D_{2000}^{2004} + D_{2010}^{2004}\right]$	-0.134	-0.134	-0.119	-0.140	-0.0709	-0.0771	-0.0467	-0.180
	[0.497]	[0.502]	[0.387]	[0.321]	[0.469]	[0.470]	[0.412]	[0.280]
	(3.874)	(4.327)	(3.905)	(4.267)	(3.517)	(4.240)	(4.326)	(4.240)
$BR_m \cdot D_{2000}^{2010}$	0.0408	0.0317	-0.0374	-0.0482	0.125	0.0993	0.0204	-0.156
	[0.523]	[0.532]	[0.372]	[0.312]	[0.529]	[0.525]	[0.375]	[0.323]
	(7.742)	(8.403)	(7.380)	(8.240)	(6.572)	(7.525)	(6.500)	(7.525)
Observations	11,034	11,029	10,922	10,892	947	944	944	944
Year/Area fixed effects	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Bartik		$\surd$	$\surd$	$\surd$		$\surd$	$\surd$	$\surd$
Demo. controls			$\surd$	Adj. $y_{m,t}$			$\surd$	Adj. $y_{m,t}$

Notes: ***, **, *, denote statistical significance at the 1%, 5% and 10% level, respectively. Robust standard errors, clustered by Canton, are given in parentheses. Each row reports the coefficient of a regression of the average log hourly wage in a location and year on the share of new immigrants, $(IM_{m,t}/TOTEMP_{m,t})$, on the total workforce. In row 1 in each panel the share of new immigrants is instrumented with two separate dummies for the Phase 1 and Phase 2 of the reform, $BR_m \times D_{2000}^{2004}$ and $BR_m \times D_{2004}^{2010}$. In row 2, the new immigrant share is instrumented with only 1 interaction term for both Phase 1 and Phase 2, $BR_m \times D_{2000}^{2010}$. F-statistics of the first stage is given below the standard errors of each regression in round brackets. Regressions are weighted using the group specific workforce of cells.

Table A.14: Difference-in-Difference Analysis of the Effect of the Opening on Log Total Hours of Earlier Immigrants, by Education Group

Area level	Municipality			Commuting zone		
	(1)	(2)	(3)	(4)	(5)	(6)
A. Dependent variable: Log total hours of highly educated						
$BR_m \times D_{2000}^{2004}$	0.00929	0.00944	-0.0161	-0.0438	-0.0422	-0.0700
	[0.100]	[0.101]	[0.0672]	[0.0821]	[0.0827]	[0.0428]
$BR_m \times D_{2004}^{2010}$	0.215	0.216	0.0394	0.118	0.120	-0.0432
	[0.144]	[0.144]	[0.109]	[0.106]	[0.106]	[0.0775]
Observations	6,868	6,867	6,826	905	904	904
R-squared	0.951	0.951	0.968	0.967	0.967	0.981
B. Dependent variable: Log total hours of middle educated						
$BR_m \times D_{2000}^{2004}$	-0.0152	-0.0373	-0.0423	-0.0763	-0.0934	-0.0947
	[0.0395]	[0.0404]	[0.0419]	[0.0503]	[0.0492]*	[0.0405]**
$BR_m \times D_{2004}^{2010}$	-0.0482	-0.0752	-0.0443	-0.122	-0.142	-0.0782
	[0.0585]	[0.0593]	[0.0541]	[0.0729]	[0.0717]*	[0.0524]
Observations	10,666	10,663	10,548	945	943	943
R-squared	0.948	0.948	0.958	0.967	0.967	0.975
C. Dependent variable: Log total hours of low educated						
$BR_m \times D_{2000}^{2004}$	0.0122	0.0109	0.0201	-0.0794	-0.0787	-0.0504
	[0.0322]	[0.0329]	[0.0451]	[0.0547]	[0.0523]	[0.0290]*
$BR_m \times D_{2004}^{2010}$	-0.00701	-0.00803	-0.00664	-0.0844	-0.0834	-0.0603
	[0.0668]	[0.0694]	[0.0600]	[0.0777]	[0.0768]	[0.0539]
Observations	11,034	11,029	10,922	947	944	944
R-squared	0.907	0.907	0.931	0.943	0.943	0.961
Year/Area fixed effects	√	√	√	√	√	√
Bartik		√	√		√	√
Demo. controls			√			√

Notes: ***, **, *, denote statistical significance at the 1%, 5% and 10% level, respectively. Robust standard errors, clustered by Canton, are given in parentheses. BR_m is one for municipalities (commuting zones) in the border region. D_{2000}^{2004} and D_{2004}^{2010} are dummies for the differential opening in *Phase 1*, from 1999 to 2004, and *Phase 2*, from 2004 to 2010, respectively. Regressions are weighted using the group specific workforce of cells.

Table A.15: 2SLS Estimates of the Effect of New Immigrant Growth on the Change in Hours Worked of Natives (Per Initial Total Employment), by Education Group

Area level	Municipality			Commuting zone		
Instrument(s)	(1)	(2)	(3)	(4)	(5)	(6)
A. Dependent variable: Change in total hours worked by highly educated						
$BR_m \cdot \left[D_{1998}^{2004} + D_{2010}^{2004}\right]$	0.926	1.081	1.428	0.475	0.558	0.812
	[0.659]	[0.750]	[0.849]	[0.513]	[0.587]	[0.410]*
	(4.997)	(4.662)	(4.493)	(4.837)	(4.781)	(6.516)
$BR_m \cdot D_{1998}^{2010}$	0.957	1.176	1.336	0.0286	0.102	0.420
	[0.899]	[1.012]	[0.808]	[0.488]	[0.521]	[0.290]
	(4.178)	(3.986)	(4.550)	(5.437)	(5.685)	(8.721)
Observations	8,365	8,365	8,364	841	841	841
B. Dependent variable: Change in total hours worked by middle educated						
$BR_m \cdot \left[D_{1998}^{2004} + D_{2010}^{2004}\right]$	0.548	0.681	-1.341	-1.061	-1.129	-1.891
	[1.580]	[1.463]	[1.071]	[1.024]	[1.006]	[1.339]
	(7.148)	(6.160)	(4.019)	(4.775)	(4.293)	(5.319)
$BR_m \cdot D_{1998}^{2010}$	-1.377	-1.247	-3.144	-3.270	-3.328	-3.659
	[2.844]	[2.715]	[2.185]	[2.310]	[2.355]	[2.457]
	(5.443)	(4.987)	(5.130)	(3.767)	(3.584)	(5.755)
Observations	9,395	9,395	9,386	842	842	842
C. Dependent variable: Change in total hours worked by low educated						
$BR_m \cdot \left[D_{1998}^{2004} + D_{2010}^{2004}\right]$	-0.652	-0.581	0.678	-0.225	-0.246	0.596
	[0.369]*	[0.358]	[0.723]	[0.337]	[0.356]	[0.470]
	(5.831)	(5.968)	(2.090)	(5.399)	(4.779)	(3.392)
$BR_m \cdot D_{1998}^{2010}$	-0.438	-0.456	0.295	-0.874	-0.867	-0.724
	[1.545]	[1.739]	[1.407]	[1.206]	[1.173]	[1.088]
	(1.014)	(0.923)	(0.659)	(1.784)	(2.052)	(1.588)
Observations	8,623	8,623	8,617	842	842	842
Year/Area fixed effects	√	√	√	√	√	√
Bartik		√	√		√	√
Demo. controls			√			√

Notes: ***, **, *, denote statistical significance at the 1%, 5% and 10% level, respectively. Robust standard errors, clustered by Canton, are given in parentheses. Each row reports the coefficient of a regression of the change in total hours worked by group $G \in \{\text{high, middle, low}\}$ on the change in the number of new immigrants, both standardised by the total initial workforce, as specified in equation (2.8). In row 1 the growth of new immigrants is instrumented with two separate dummies for the Phase 1 and Phase 2 of the reform, $BR_m \times D_{1998}^{2004}$ and $BR_m \times D_{2004}^{2010}$. In row 2, the new immigrant growth is instrumented with only 1 interaction term for both Phase 1 and Phase 2, $BR_m \times D_{1998}^{2010}$. F-statistics of the first stage is given below the standard errors of each regression in round brackets. Regressions are weighted using the group specific workforce of cells at the beginning of the period.

Table A.16: 2SLS Estimates of the Effect of New Immigrant Growth on the Change in Hours Worked of Earlier Immigrants (Per Initial Total Employment), by Education Group

Area level	Municipality			Commuting zone		
Instrument(s)	(1)	(2)	(3)	(4)	(5)	(6)
	A. Dependent variable: Change in total hours worked by highly educated					
$BR_m \cdot [D_{1998}^{2004} + D_{2010}^{2004}]$	0.154	0.211	0.472	0.0242	0.0556	0.351
	[0.180]	[0.208]	[0.252]*	[0.102]	[0.113]	[0.194]*
	(1.827)	(1.529)	(1.302)	(3.439)	(3.568)	(2.897)
$BR_m \cdot D_{1998}^{2010}$	0.263	0.317	0.476	0.0141	0.0389	0.289
	[0.222]	[0.261]	[0.252]*	[0.115]	[0.128]	[0.178]
	(2.673)	(2.196)	(2.594)	(6.190)	(6.392)	(5.717)
Observations	4,500	4,500	4,488	781	781	781
R-squared	0.323	0.142	-0.566	0.192	0.214	-0.480
	B. Dependent variable: Change in total hours worked by middle educated					
$BR_m \cdot [D_{1998}^{2004} + D_{2010}^{2004}]$	-0.0489	0.0590	-0.184	-0.0327	-0.00659	-0.0840
	[0.301]	[0.282]	[0.250]	[0.273]	[0.254]	[0.230]
	(3.497)	(3.634)	(3.709)	(5.532)	(5.345)	(5.743)
$BR_m \cdot D_{1998}^{2010}$	0.570	0.632	0.463	0.0210	0.0465	0.0606
	[0.827]	[0.717]	[0.677]	[0.413]	[0.379]	[0.359]
	(1.741)	(1.737)	(2.161)	(5.505)	(5.123)	(5.032)
Observations	7,761	7,761	7,711	837	837	837
R-squared	0.130	0.098	0.157	0.114	0.140	0.268
	A. Dependent variable: Change in total hours worked by low educated					
$BR_m \cdot [D_{1998}^{2004} + D_{2010}^{2004}]$	0.315	0.424	0.238	0.159	0.138	0.108
	[0.472]	[0.471]	[0.569]	[0.442]	[0.473]	[0.335]
	(3.313)	(3.527)	(2.121)	(5.042)	(4.257)	(4.326)
$BR_m \cdot D_{1998}^{2010}$	-4.408	-4.669	-4.343	-0.00911	-0.00459	-0.120
	[10.77]	[12.99]	[11.10]	[0.735]	[0.741]	[0.578]
	(0.217)	(0.170)	(0.228)	(2.150)	(2.452)	(3.061)
Observations	7,998	7,998	7,957	841	841	841
R-squared	-59.705	-66.402	-58.268	0.084	0.088	0.125
Year/Area fixed effects	√	√	√	√	√	√
Bartik		√	√		√	√
Demo. controls			√			√

Notes: ***, **, *, denote statistical significance at the 1%, 5% and 10% level, respectively. Robust standard errors, clustered by Canton, are given in parentheses. Each row reports the coefficient of a regression of the change in total hours worked by group $G \in \{\text{high, middle, low}\}$ on the change in the number of new immigrants, both standardised by the total initial workforce, as specified in equation (2.8). In row 1 the growth of new immigrants is instrumented with two separate dummies for the Phase 1 and Phase 2 of the reform, $BR_m \times D_{1998}^{2004}$ and $BR_m \times D_{2004}^{2010}$. In row 2, the new immigrant growth is instrumented with only 1 interaction term for both Phase 1 and Phase 2, $BR_m \times D_{1998}^{2010}$. F-statistics of the first stage is given below the standard errors of each regression in round brackets. Regressions are weighted using the group specific workforce of cells at the beginning of the period.

Table A.17: 2SLS Estimates of the Effect of New Immigrants on the Distribution of Earlier Immigrant Workers Across Different Management Levels within Education Groups

Area level	Municipality				Commuting zone			
Dependent Variable (Group Share in 1998)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				A. Highly educated				
Share in high manag.	0.114	0.113	-0.144	0.273	0.0214	0.0111	-0.752	0.461
(0.189)	[0.790]	[0.787]	[0.852]	[0.894]	[0.928]	[0.929]	[1.176]	[1.096]
Share in middle manag.	0.413	0.410	0.465	0.277	0.335	0.319	0.989	0.0915
(0.215)	[0.731]	[0.740]	[0.791]	[0.834]	[0.809]	[0.833]	[1.046]	[0.870]
Share in low manag.	0.270	0.273	0.437	0.293	0.581	0.589	1.094	0.410
(0.281)	[0.935]	[0.938]	[0.957]	[0.910]	[0.808]	[0.822]	[1.032]	[0.831]
Share in no manag.	-0.797	-0.796	-0.757	-0.843	-0.938	-0.919	-1.331	-0.963
(0.315)	[0.710]	[0.714]	[0.717]	[0.673]	[0.574]	[0.582]	[0.703]*	[0.545]*
Observations	6,837	6,836	6,795	6,561	905	904	904	904
R-squared	0.434	0.434	0.437	0.429	0.375	0.377	0.376	0.371
F-stats	11.42	11.68	10.04	12.00	10.37	10.84	10.61	10.84
				B. Middle educated				
Share in high manag.	-0.0658	-0.0444	-0.0491	-0.0872	-0.178	-0.157	-0.240	-0.180
(0.018)	[0.192]	[0.185]	[0.204]	[0.195]	[0.234]	[0.228]	[0.328]	[0.260]
Share in middle manag.	0.167	0.105	0.0856	0.236	0.192	0.157	0.226	0.275
(0.04)	[0.303]	[0.257]	[0.282]	[0.359]	[0.348]	[0.310]	[0.362]	[0.408]
Share in low manag.	0.134	0.274	0.305	0.456	0.0797	0.288	0.275	0.685
(0.228)	[0.502]	[0.447]	[0.457]	[0.380]	[0.426]	[0.402]	[0.485]	[0.400]*
Share in no manag.	-0.235	-0.334	-0.342	-0.605	-0.0935	-0.288	-0.261	-0.780
(0.714)	[0.677]	[0.587]	[0.615]	[0.680]	[0.612]	[0.562]	[0.712]	[0.656]
Observations	10,574	10,571	10,459	10,303	944	942	942	942
R-squared	0.394	0.392	0.398	0.361	0.513	0.513	0.527	0.419
F-stats	11.12	13.11	11.39	12.94	8.593	9.479	6.782	9.479
				C. Low educated				
Share in high manag.	-0.0853	-0.0917	-0.113	-0.0851	-0.0797	-0.0847	-0.110	-0.0819
(0.003)	[0.0584]	[0.0634]	[0.0734]	[0.0719]	[0.0678]	[0.0662]	[0.0817]	[0.0679]
Share in middle manag.	-0.00839	-0.0119	-0.0236	-0.0300	0.0205	0.0182	0.0121	-0.0271
(0.003)	[0.0631]	[0.0636]	[0.0702]	[0.0669]	[0.0697]	[0.0682]	[0.0817]	[0.0792]
Share in low manag.	0.856	0.894	0.859	0.801	0.989	1.024	1.298	1.043
(0.076)	[0.575]	[0.597]	[0.601]	[0.610]	[0.649]	[0.683]	[0.866]	[0.765]
Share in no manag.	-0.762	-0.790	-0.723	-0.686	-0.930	-0.957	-1.200	-0.934
(0.918)	[0.597]	[0.622]	[0.630]	[0.634]	[0.699]	[0.738]	[0.918]	[0.820]
Observations	10,934	10,929	10,829	10,730	947	944	944	944
R-squared	0.269	0.263	0.287	0.291	0.255	0.254	0.186	0.221
F-stats	7.592	8.283	7.369	8.138	6.572	7.524	6.533	7.524
Year/Area fixed effects	√	√	√	√	√	√	√	√
Bartik		√	√	√		√	√	√
Demo. controls			√	Adj. $y_{m,t}$			√	Adj. $y_{m,t}$

Notes: ***, **, *, denote statistical significance at the 1%, 5% and 10% level, respectively. Robust standard errors, clustered by Canton, are given in parentheses. Each row reports the coefficient of a regression of the share of a management level on the total workforce of an education group in a location and year on the share of new immigrants, $(IM_{m,t}/TOTEMP_{m,t})$, on the total workforce. The new immigrant share is instrumented with only 1 interaction term for both Phase 1 and Phase 2, $BR_m \times D_{2000}^{2010}$. F-statistics of the first stage is the same for each management level among an education group. Regressions are weighted using the group specific workforce of cells.

Table A.18: 2SLS Estimates of the Effect of New Immigrants on the Distribution of Earlier Immigrant Workers Across Jobs With Different Task Content Within Education Groups

Area level	Municipality				Commuting zone			
Dependent variable (Group Share in 1998)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Highly educated								
Share in complex tasks	-0.483	-0.498	-0.641	-0.344	-0.563	-0.616	-1.040	-0.384
(0.225)	[0.629]	[0.599]	[0.669]	[0.604]	[0.601]	[0.584]	[0.744]	[0.689]
Share in intermediate tasks	-0.0787	-0.0628	0.0604	-0.0291	-0.173	-0.121	0.226	-0.0792
(0.747)	[0.881]	[0.841]	[0.893]	[0.780]	[0.782]	[0.763]	[0.878]	[0.879]
Share in routine tasks	0.562	0.561	0.580	0.374	0.736	0.738	0.815	0.463
(0.029)	[0.560]	[0.560]	[0.614]	[0.398]	[0.511]	[0.519]	[0.644]	[0.425]
Observations	6,864	6,863	6,822	6,586	903	902	902	902
R-squared	0.361	0.361	0.359	0.343	0.197	0.197	0.194	0.121
F-stats	11.46	11.73	10.11	11.92	10.37	10.85	10.61	10.85
B. Middle educated								
Share in complex tasks	0.144	0.159	0.160	0.109	0.112	0.124	0.148	0.0987
(0.016)	[0.194]	[0.180]	[0.191]	[0.163]	[0.184]	[0.177]	[0.230]	[0.172]
Share in intermediate tasks	-1.479	-1.454	-1.481	-0.793	-1.636	-1.632	-2.055	-1.011
(0.847)	[0.925]	[0.839]*	[0.846]*	[0.602]	[1.025]	[0.969]	[1.153]*	[0.686]
Share in routine tasks	1.335	1.294	1.321	0.683	1.524	1.508	1.908	0.912
(0.137)	[0.946]	[0.852]	[0.844]	[0.636]	[1.028]	[0.964]	[1.129]	[0.699]
Observations	10,657	10,654	10,539	10,381	945	943	943	943
R-squared	0.140	0.151	0.160	0.245	0.095	0.101	0.021	0.169
F-stats	11.22	13.26	11.50	13.15	8.603	9.489	6.798	9.489
C. Low educated								
Share in complex tasks	0.0567	0.0517	0.0529	0.0339	0.0577	0.0542	0.0361	0.0352
(0.001)	[0.0687]	[0.0620]	[0.0726]	[0.0750]	[0.0889]	[0.0829]	[0.0946]	[0.0865]
Share in intermediate tasks	0.391	0.414	0.424	0.520	0.561	0.588	0.906	0.625
(0.265)	[0.663]	[0.648]	[0.631]	[0.626]	[0.928]	[0.898]	[0.972]	[0.870]
Share in routine tasks	-0.448	-0.465	-0.476	-0.553	-0.619	-0.643	-0.942	-0.660
(0.734)	[0.632]	[0.628]	[0.617]	[0.614]	[0.878]	[0.857]	[0.944]	[0.838]
Observations	11,025	11,020	10,913	10,814	947	944	944	944
R-squared	0.374	0.373	0.408	0.355	0.302	0.303	0.338	0.267
F-stats	7.689	8.417	7.358	8.231	6.572	7.524	6.533	7.524
Year/Area fixed effects	√	√	√	√	√	√	√	√
Bartik		√	√	√		√	√	√
Demo. controls			√	Adj. $y_{m,t}$			√	Adj. $y_{m,t}$

Notes: ***, **, *, denote statistical significance at the 1%, 5% and 10% level, respectively. Robust standard errors, clustered by Canton, are given in parentheses. Each row reports the coefficient of a regression of the share of a task group on the total workforce of an education group in a location and year on the share of new immigrants, $(IM_{m,t}/TOTEMP_{m,t})$, on the total workforce. The new immigrant share is instrumented with only 1 interaction term for both Phase 1 and Phase 2, $BR_m \times D_{2000}^{2010}$. F-statistics of the first stage is the same for each task group among an education group. Regressions are weighted using the group specific workforce of cells.

2.B Data Appendix

2.B.1 Construction of total local adjusted employment and average log hourly wages

To construct an adjusted wage outcome measures cleaned from the effect of individual, demographic characteristics, we follow a procedure suggested by Peri and Sparber (2009). We regress the log hourly wages of individual workers on a full set of age dummies (46 dummies), dummies for the education level (2 dummies), marital status, gender and tenure and tenure squared.

$$\begin{aligned} y_{i,n,t} &= \alpha_{n,t} + \sum_{a=18}^{64} \beta_{a,n,t} \left(AGE_{i,n,t} = a \right) + \gamma_{n,t} EDU^{M}_{i,n,t} + \delta_{n,t} EDU^{H}_{i,n,t} \\ &\quad + \phi_{n,t} TEN_{i,n,t} + \psi_{n,t} TEN^{2}_{i,n,t} + \eta_{n,t} MAR_{i,n,t} + \rho_{n,t} GEN_{i,n,t} + \epsilon_{i,n,t} \end{aligned}$$

where $y_{i,n,t}$ is the log hourly wage of individual i with nationality $n \in \{\text{natives}, \text{earlier immigrants}\}$ in wave t. We do this regressions separately for natives and earlier immigrant in each year.[52] Then, we subtract an individuals predicted wage from its actual outcome. This residual represents an individual's wage cleaned form demographic effects. Finally, we collapse the data on the level or municipalities or commuting zones to get the average of the adjusted log hourly wage using each individuals survey weight.

[52] In the wage regressions we exclude wages above the 99th percentile.

3 Which Factors Drive the Skill-Mix of Migrants in the Long-Run?

Joint with Ronald Indergand

3.1 Introduction

Which factors drive the skill composition of immigrants? A pervasive feature of international migration flows to developed countries in the last decades is that newly arriving immigrants are increasingly highly skilled. Between 1980 and 2010, the share of immigrants with a tertiary education increased by 15 percentage points on average for 20 OECD countries (Brücker H. and Marfouk, 2013).[1] Yet, the changes in the share of highly educated immigrants have been very uneven across countries with large gains in countries such as Australia, Canada, the UK and Switzerland and more modest changes in France or Germany (Docquier and Marfouk, 2005). These trends have gained more saliency in the light of an ongoing discussion among policy makers whether skilled immigration could serve as a palliative for increasing labour shortages of skills in developed countries. Yet, there seems to be little agreement on the actual drivers of skill scarcity and whether and how policy makers should respond by adapting immigration policies (Chaloff and Lemaitre, 2009; Stevens et al., 2009). From this perspective, it is surprising that the factors driving these trends have received relatively scant attention in the academic literature.

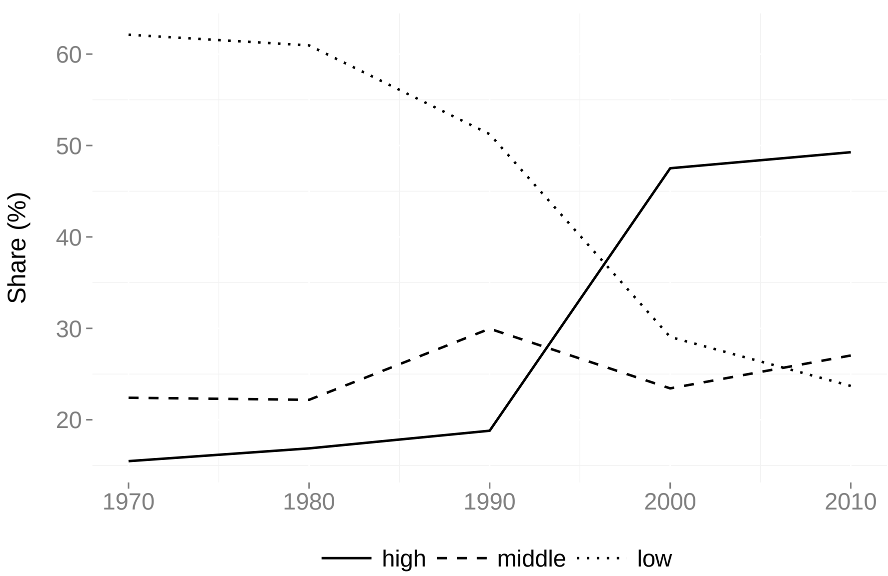
In this paper, we study the determinants of the changing skill composition among immigrants building on the empirical framework suggested by Grogger and Hanson (2011). According to this framework, the educational composition of immigrants from a certain origin country observed in a destination depends on (i) the wage differentials of education groups in the destination, (ii) the wage differentials in the origin country, (iii) the population shares of the education groups in the origin and (iv) education specific bilateral migration costs. While Grogger and Hanson (2011)'s analysis is static using a cross-section of destinations and origin countries, we analyse the importance of each of

[1] The countries in the IAB's brain drain data are Australia, Austria, Canada, Chile, Denmark, Finland, France, Germany, Greece, Ireland, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, and United States.

these factors from a long-run perspective. We focus on the period between 1980 and 2010, and on a single destination country, Switzerland.

Switzerland represents an interesting and exemplary case for a number of reasons. First, together with a group of other countries (such as Australia, Canada and the U.S.) Switzerland has traditionally exhibited very high immigration rates (Peri, 2005). In 2011, the country's population share of foreign born was at 27.2% which was only surpassed by Luxembourg (OECD, 2014). Second, Switzerland has witnessed a strong change in the skill composition of newly immigrating workers during the past decades. In 1990, only 17% of those workers, who recently (within the last five years) immigrated into the country had a tertiary degree, whereas this share rose to 47% in 2010 (cf. figure 3.1).[2] Third, the integration of Switzerland into the European labour market provides us with a rare policy experiment in which immigration restrictions were abolished for workers from the EU while immigration from third party countries remained being subject to quotas. This allows studying the effect of changing immigration restrictions by comparing changes in the skill mix of EU immigrants with those of Non-EU immigrants.

Figure 3.1: Evolution of Education Group Shares of Newly Arriving Immigrants in Switzerland, 1970 - 2010



Notes: Newly arriving immigrants are foreign born individuals having lived abroad 5 years prior to the Census year. High educated workers are those with a tertiary education level, middle educated are secondary educated and low educated have compulsory education or less. See Section 3.3 for details. Employment data from Swiss Census 1970 - 2010.

[2]The immigration influx was substantial also in absolute numbers, increasing the stock of highly educated foreign employees from 100,000 to 400,000 (in relation to a total workforce of roughly 4 million, see e.g. Favre et al., 2013).

To analyse the role of the different driving forces of the skill composition of immigrants, we exploit the variation in the change of three education group shares (tertiary, secondary, compulsory and less education) among newly arriving immigrants from 30 different origin countries in 106 local labour markets in Switzerland between 1980 and 2010. The fundamental challenge to the econometrician is the likely endogeneity of educational wage differentials to the influx of immigrants with different educational backgrounds, a point which has not been sufficiently acknowledged in the literature on cross-country immigration flows.[3] We deal with this concern by using a proxy for shifts to the local relative demand for workers with different educational backgrounds which is orthogonal to immigration inflows. In particular, as suggested by Autor and Dorn (2013), we exploit that local labour markets with a higher specialisation in routine occupations due to their industry structure in 1970 experienced stronger adoption of computer/automation capital in later decades. In turn, more technology adoption lead to a more pronounced polarisation of the wage and employment structure in these local labour markets. The basic idea is, that the adoption of computer capital substituted for workers in occupations with a high routine task content lowering their wages and their employment while increasing wages and employment of workers with complementary skills in high-skill abstract occupations and low-skill non-routine manual occupations. As Michaels et al. (2014) show, this polarisation of the labour demand goes hand in hand with a polarisation of the demand for education, as broad occupations groups correspond closely with education levels.[4] Consequently, the share of routine employment of a local labour market in the pre-1980 area serves as a good proxy for exogenous changes to the relative demand for workers with different educational backgrounds during the computerisation area starting around 1980.[5] In principle, relative demand for workers with different educational backgrounds could also be driven by other demand shifters, e.g. offshoring. Yet, the existing evidence suggests that technology has been *the* major source of wage changes in the developed world (Katz and Autor, 1999).[6]

Our empirical analysis provides two main results. First, we find that two factors in the framework suggested by Grogger and Hanson (2011) stand out as the main drivers of

[3]See Mayda (2010) for a notable exception and discussion

[4]As we show in Section 3.3, workers with tertiary education are overrepresented in non-routine abstract occupations and workers with low educational backgrounds are overrepresented in low skill service occupations while workers with a middle educational background overwhelmingly work in routine occupations.

[5]The routine share has been widely employed in the literature on job polarisation as a proxy for relative demand shifts induced by technology. See e.g. Goos et al. (2009), Goos et al. (2010) or Autor and Dorn (2013). Acemoglu and Autor (2011) provide an extensive overview of the relevant literature.

[6]We document the importance of routinisation and other drivers of the relative demand for workers with different education background in the robustness section of our results.

the skill composition of newly arriving immigrants: Trends in education supply in origin countries and the relative demand for skills in destinations. Our findings show, that a 1 percentage point increase in the share of an education group in the origin country leads to a close to 1:1 increase in the shares of highly and middle educated workers and a slightly lower increase in the share of low educated workers. However, education supply can only explain a fraction of the observed changes in destinations in the case of highly educated workers and mis-predicts the sign of the average change in the case of middle educated workers. This underscores the importance of accounting for the role of relative demand. Confirming our expectation, we estimate a positive effect of routinisation on the share of highly educated workers, a negative effect on the share of immigrants with a middle education whereas the point estimate for low educated immigrant workers cannot be distinguished from zero. This emphasises the role of technological change as a particular source for demand driven immigration. Taken together, supply and demand slightly over-predict the observed change in the share of highly educated workers in Swiss destinations while explaining the small decrease in the share of middle educated workers and the larger loss of low educated workers relatively precisely. These estimates are very robust to controlling for a host of alternative explanations which might drive changes to the skill composition of immigrants. In particular, we show that accounting for origin country changes in educational wage differentials, changes to the income distribution and controlling for the general performance of the economy (proxied by changes to GDP per capita in PPP) does not affect our estimated coefficients. Furthermore, we show that the effect of routinisation is also robust to controlling for ethnic networks, which are generally regarded as a powerful pull-driver of immigration (Bartel, 1989; Card, 2001). We find that ethnic networks are particularly important for low educated immigrants while having no effect on highly educated workers. In addition, we show that relative demand shifts induced by routinisation are the most powerful demand factor explaining the change in the skill composition of immigrants, while alternative determinants of the relative demand, such as offshoring, are less important. This adds to the literature showing similar findings for natives or the general workforce (Autor et al., 2013b; Goos et al., 2011; Michaels et al., 2014).

As a second main finding, our results suggest that the integration of Switzerland into the European labour market after 2002 had, if anything, an adverse effect on the skill composition of migrants. That is, the increase in the share of highly educated workers from the EU was lowered relative to those from other countries. In contrast, the decrease of the share of low educated workers was attenuated for workers from the EU relative to those from other countries. To identify the effect of the labour market integration, we use a difference-in-difference estimator comparing changes in the education shares of immigrants from the EU to those of other countries for which immigration restrictions were not relaxed after 2002 while controlling for economic drivers. As may be expected, we find that the effect of lowering immigration restrictions on the skill composition was strongest in case of old EU member states, for which immigration quotas were phased-out completely already in 2007.[7] In contrast, the effect is not distinguishable from zero in case of new EU member states for which some quotas were kept in place until 2011. These estimates are robust to controlling for country group specific trends, and earlier country group specific immigration restrictions.

The related literature on the effect of a change in immigration restrictions on the skill composition of immigrants is rather scarce. Kato and Sparber (2013) show that the reduction of available H1B visas for skilled workers in 2003 had a negative effect on the quality of student applications to U.S. universities. They argue that the reduced working opportunities after graduation might have deterred high ability students more than lower ability students who would not have been able to apply for an H1B visa anyway. Huber and Bock-Schappelwein (2014), on the other hand, find that Austria's accession to the European Economic Area (EEA) in 1994 and the associated integration of the labour market reduced the share of poorly educated immigrants from the EU compared to other countries. As Huber and Bock-Schappelwein (2014) point out, immigrants to Austria prior to 1994 were negatively selected due to the low returns to education in Austria compared to other European countries. Thus, the liberalisation of the labour market access had the strongest effect on middle skilled foreign workers for whom the net benefits of immigration were close to zero before and positive thereafter. We interpret these findings such that in Switzerland, in contrast to Austria, immigrants were already very positively selected prior to the accession to the EU labour market. Thus, net benefits of immigration were positive for highly skilled immigrants whereas the net benefits were close to zero for middle skilled and negative for poorly skilled. Consequently, the relaxation of immigration restrictions had the strongest effect on foreign workers at the lower tail of the skill distribution.[8]

We build on a large literature on the selection of immigrants, i.e. which workers along the skill distribution find it most beneficial to migrate and how this affects the scale of immigration to destinations. In his seminal contribution, Borjas (1987, 1999) shows that

[7]The cautious interpretation of this effect has to acknowledge the fact that applicants for residency permits from non-EU countries have been subject to quotas and skill requirements since the early 1990s: "*In deciding whether to grant residence permits, the professional qualifications of applicants and their professional and social adaptability, language skills and age must also indicate that there is a prospect of lasting integration in the Swiss job market and the social environment*" (Bundesbehörden, 2014). Thus, this effect is the difference in the policy treatment of immigrant workers from EU origin countries, which changed in 2002, compared to the policy treatment of non-EU workers for which the immigration policy remained constant since 1991.

[8]The arguments used here assume a monotone relationship between the net benefits of immigration and skills like in Borjas (1987, 1999).

immigrants are positively selected if the returns to education are higher in the destination than in the origin country and negatively selected in the opposite case. Then, changes to the general wage level, the return to education and changes to migration costs in the destination relative to the origin country affect which parts of the skill distribution of workers in the origin country find it beneficial to migrate. Based on this framework, Mayda (2010) and Ortega and Peri (2013) analyse the effect of economic drivers and changes to the immigration restriction on the general magnitude of immigration between different countries and to the U.S. (see also Clark et al., 2007). Most closely, however, our paper links to Grogger and Hanson (2011) who study the relative stock of immigrants with different educational backgrounds from various origin countries in a cross-section of destination countries. While finding that destinations with higher wage differentials experience more positive sorting, i.e. they have a higher share of highly educated workers from a particular origin country, their analysis remains essentially silent on the fact where higher wage differentials across destinations might originate from and how sorting changes over time.

Our paper is also related to the literature on routinisation and directed technical change. We show that changes in long-run labour demand triggered by technological change may have major implications on the international migration flows, in particular its skill composition. This aspect has only been cautiously mentioned in the seminal contribution of Autor and Dorn (2013) and not gained much attention otherwise. Furthermore, our findings show that long-run labour demand changes, such as routinisation, have very persistent and local nature which underscores Borjas (2001)'s critique of the part of the immigration literature which treats past-settlement of immigrants as orthogonal to current changes in labour demand.

The remainder of this papers is organised as follows. Section 3.2 gives a short motivation of the theoretical framework and introduces the empirical strategy. Section 3.3.1 and 3.3.2 discuss the data and the routinisation measure. Section 3.3.3 establishes a series of stylised facts about employment and wage polarisation in Switzerland and points at a set of interesting differences between native and immigrant workers. Subsequently, the findings of the empirical analysis are discussed in Section 3.4. Section 3.5 concludes.

3.2 Conceptual Framework and Empirical Approach

In this section, we illustrate the forces driving the immigration decision of workers with different educational backgrounds using a simple model of immigrants' self-selection based on income maximisation in the fashion of Roy (1951). Using Grogger and Hanson (2011)'s adaption of the Roy model to three education groups (low, middle and high), we derive sorting equation which explain why different destinations receive immigrants with different educational backgrounds. Subsequently, we explain how we identify the different factors using variation across local labour markets, origin countries and time and take our sorting equation to the data in Section 3.3.

3.2.1 Sorting of Immigrants Across Local Labour Markets

We consider the stock of migrant workers from many origin countries in many destinations. The basic ingredient in Grogger and Hanson (2011)'s adaption of the Roy model are separate migration decisions of workers with primary, secondary and tertiary education. Specifically, worker i with education e from origin country o evaluates the utility from migrating to destination j based on the following linear utility function

$$U^e_{i,o,j} = \alpha\left(W^e_{i,j} - C^e_{i,o,j}\right) + \epsilon^e_{i,o,j} \tag{3.1}$$

where $W^e_{i,j}$ and $C^e_{i,o,j}$ are education specific wages and migration costs, respectively, and $\epsilon^e_{i,o,j}$ is an unobserved idiosyncratic term. The wage of worker i is given by

$$W^e_{i,o,j} = \exp\left(\mu_j + \delta^e_j D^2_i + \delta^3_j D^3_i\right)$$

where $\exp(\mu_j)$ is the wage of a primary educated worker and δ^2_j (δ^3_j) is the return to secondary (tertiary) education and $D^e_i = 1$ if worker has education level e. Migrating from origin county o to destination j is a function of fixed costs $f_{o,j}$ and education specific costs $g^e_{o,j}$:

$$C^e_{i,o,j} = f_{o,j} + g^1_{o,j}D^1_i + g^2_{o,j}D^2_i + g^3_{o,j}D^3_i$$

Grogger and Hanson (2011) take Equation (3.1) as a first-order approximation of a more general utility function with $\alpha > 0$ as the marginal utility of income.[9] Staying in the origin country is modelled as the migration costs being zero. We follow the literature (Grogger and Hanson, 2011; McFadden, 1974) assuming that errors, $\epsilon^e_{i,o,j}$, follow an i.i.d. extreme-value distribution.[10] Then, assuming that agents base their decision of whether

[9] Grogger and Hanson (2011) also derive predictions using log-utility functions in the fashion of Borjas (1987, 1999). In their empirical analysis, however, they show that both linear and log-utility lead to very similar predictions of parameters in the sorting equation, on which we focus here. The reasons is, as they argue, that sorting on log differences in wages is very similar to sorting on level differences in wages in a sample of destinations with similar labour productivity.

[10] This specification of the disturbance term assumes that *independence of irrelevant alternatives* (IIA) applies among destinations. In our empirical application, we consider different local labour markets within Switzerland as destinations, thus we need only that IIA applies within to the destinations in the sample (Grogger and Hanson, 2011). This assumption is supported by Borjas (2001) who shows that conditional on having arrived in certain country, immigrants pick the location which offers the highest reward for their particular skill. As Grogger and Hanson (2011) show, we can test this assumption by

and where to emigrate maximising their utility, we can write the log odds of migrating to destination j versus staying in the origin-country o for a worker with education level e as

$$\ln \frac{L^e_{o,j}}{L^e_o} = \alpha\left(W^e_j - W^e_o\right) - \alpha f_{o,j} - \alpha g^e_{o,j} \tag{3.2}$$

where $L^e_{o,j}$ constitutes the population share of workers with education level e from origin country o in destination j and L^e_o is the population share of workers with education e staying in o. Equation (3.2) characterises scale of immigration, i.e. the number of workers with education e who decide to emigrate to destination j from origin country o. The scale of immigration depends positively on the skill-related wage difference net of migration costs.

Now, the skill composition of immigrants in a destination j from origin country o is just the relative scale of immigration from this country of workers with different educational backgrounds. For concreteness, we can write down separate scale equations for workers with secondary ($e = M$) and tertiary education ($e = H$), take the difference and rearrange to

$$\ln \frac{L^H_{j,o}}{L^M_{j,o}} = \underbrace{\alpha\left(W^H_j - W^M_j\right)}_{\text{(i)}} - \underbrace{\alpha\left(W^H_o - W^L_o\right)}_{\text{(ii)}} - \underbrace{\left(g^H_{j,o} - g^M_{j,o}\right)}_{\text{(iii)}} + \underbrace{\ln \frac{L^H_o}{L^M_o}}_{\text{(iv)}} \tag{3.3}$$

Equation (3.3) describes the relative sorting of tertiary versus secondary educated migrant workers from origin-country o across destinations j. The relative number of highly to middle educated workers increases, (i) if the wage difference between education groups in the destination j increases, (ii) if the same difference decreases in the origin-country, (iii) if migration costs fall more for highly educated workers, or (iv) if the supply of highly educated workers increases in the origin country.

3.2.2 Empirical Approach

The sorting Equation (3.3) makes predictions about how the number of immigrants with tertiary education relative to those with secondary education from a specific origin-country o varies across destinations j. To characterise the change in sorting, we can add time indices, t, representing decades, to Equation (3.3) and take first differences

$$\Delta\left(\ln \frac{L^H}{L^M}\right)_{j,o,t} = \underbrace{\alpha\Delta\left(w^H - w^M\right)_{j,t}}_{\text{(i)}} - \underbrace{\alpha\Delta\left(w^H - w^M\right)_{o,t}}_{\text{(ii)}} - \underbrace{\Delta\left(g^H - g^M\right)_{j,o,t}}_{\text{(iii)}} + \underbrace{\Delta\left(\ln \frac{L^H}{L^M}\right)_{o,t}}_{\text{(iv)}} \tag{3.4}$$

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dropping one destination at the time in our regressions and investigating the stability of our estimated coefficients.

To take this expression to the data, we need information on wages in Swiss commuting zones, the destinations in our case, and origin-countries as well as information on the skill supply in origin countries and relative migration costs. However, one concern arising is that the change of these wage measures, $\Delta\left(w^H - w^M\right)_{j,t}$, is likely to be endogenous to immigration (see e.g. Borjas, 2001). Although a large part of the literature investigates this particular relationship, the existing literature studying drivers of immigration largely ignored this concern.[11] Instead of using local wage measures, we suggest a different route using direct proxies for local relative demand shifts which affect educational wage differentials but are not affected by immigration. A well established proxy for such local demand shifts is a region's "initial" share of routine employment, which we denoted by $RSH_{j,t}$.[12] This measure was first introduced by Autor and Dorn (2013) for local labour markets but the idea of routine intensity as a proxy for relative demand shifts affecting the wage differential of workers with different educational backgrounds and skills has found wide application in the literature on skill-biased technical change and job polarisation.[13] The basic intuition is simple. Computers (or automation capital, more generally) are a close substitute for workers employed in jobs with a large share of routine manual or routine cognitive tasks, such as assembly line workers or bank clerks. The continuously falling price of IT capital over the past decades has lead firms to substitute computers for these workers and has driven down their wages relative to other workers. On the other hand, computer capital complemented workers employed in managerial or professional occupations engaged in abstract, problem-solving tasks. Consequently, the adoption of computers increased the demand for these workers, raising their wages and employment. In this process, also the demand for occupations at the bottom of the wage and education distribution, which are primarily engaged in non-routine manual tasks (such as waiters, cleaners or security guards), increased also raising their wages and employment. Thus, labour demand polarised with wages and employment increasing at the top and at the bottom relative to the middle.[14] Indeed, Autor and Dorn (2013) show for the U.S. that

[11] One notable exception is Mayda (2010) who uses lagged income measures to investigate the scale of immigration.

[12] We explain in section 3.3 in detail, how we measure $RSH_{j,t}$.

[13] See Acemoglu and Autor (2011) for an overview of the relevant literature. After Autor et al. (2003)'s seminal contribution showing wage and employment trends of workers with different routine-task content in their jobs for the U.S. (also Autor et al. (2006, 2008)), similar trends were documented for the U.K. (Goos and Manning, 2007), Europe (Goos et al., 2009, 2011) and Germany (Dustmann et al., 2009; Spitz-Oener, 2006) showing some connection to the routine intensity.

[14] Michaels et al. (2014) demonstrate that there is a close correspondence between these occupation groups and education levels. They show that computer adoption has a positive effect on the demand for workers with a tertiary education, a negative effect on the demand of workers with a middle, secondary education while the effect on low educated with primary schooling or less is ambiguous. We demonstrate the close correspondence between education and occupation groups in section 3.3.

regions with a larger share of employment in routine occupations at the beginning of their sample, experience stronger polarisation subsequently.[15] Consequently, we expect that regions with a larger initial share of routine employment experience larger positive demand shifts for highly educated workers relative to middle educated workers inducing their wage difference to increase. In contrast, we expect these regions to experience larger negative demand shifts for middle educated workers relative to low educated workers inducing their relative wage difference to decrease. Thus, we can write down the empirical versions of the sorting equation (3.4) for highly skilled and poorly skilled workers relative to middle skilled workers where we substitute changes to wage differences in destinations with a region's routine share:

$$\Delta\left(\ln\frac{L^H}{L^M}\right)_{j,o,t} = \beta_1 RSH_{j,t} + \beta_2\Delta\left(w^H - w^M\right)_{o,t} + \beta_3\Delta\left(\ln\frac{L^H}{L^M}\right)_{o,t} + \alpha_t + \alpha_o + \alpha_c + \epsilon_{j,o,t} \tag{3.5}$$

$$\Delta\left(\ln\frac{L^M}{L^L}\right)_{j,o,t} = \beta_1 RSH_{j,t} + \beta_2\Delta\left(w^M - w^L\right)_{o,t} + \beta_3\Delta\left(\ln\frac{L^M}{L^L}\right)_{o,t} + \alpha_t + \alpha_o + \alpha_c + \epsilon_{j,o,t} \tag{3.6}$$

where Δ takes differences over decades, t, $\Delta x_t = x_{t+1} - x_t$. We include the following fixed effects to account for relative migration costs; Canton fixed-effects, α_c, control for fixed institutional backgrounds, language regions, taxes and fixed amenities on a higher regional level than j. Time fixed-effects, α_t, control for the fact that all regions and origin countries might face different circumstances in different decades. Finally, origin country fixed-effects, α_o, control for constant differences between origin-countries such as the distance to Switzerland. If the routine share of a location captures a relative demand shift for high and low educated workers relative to middle educated workers we expect that β_1 is positive in Equation (3.5) and negative in Equation (3.6). In contrast, we expect that improving labour market conditions for highly (middle) educated workers in origin countries induce their migrating numbers to decrease relatively to middle (low) educated workers ($\beta_2 < 0$). Finally, we expect the supply of each education group in origin countries to be positively correlated ($\beta_3 > 0$).

A considerable drawback of estimating Equation (3.5) and (3.6) is that the magnitude of coefficients is hard to interpret. To make things more transparent, we estimate

[15] In their framework, Autor and Dorn (2013) assume that capital is fixed across regions, while labour is mobile. Empirically, this assumption translates into an IV strategy exploiting only the routine specialisation of local labour markets based on their industry specialisation prior to computerisation, i.e. 1970 in our case. See the discussion in section 3.4.

specifications similar to those of Autor and Dorn (2013):

$$\begin{aligned} \Delta EDUSH^E_{j,o,t} &= \beta^E_1 RSH_{j,t} + \beta^E_2 \Delta X^E_{o,t} + \beta^E_3 \Delta EDUSH^E_{o,t} \\ &\quad + \alpha_t + \alpha_o + \alpha_c + \epsilon_{j,o,t} \end{aligned} \tag{3.7}$$

where $\Delta EDUSH^E_{j,o,t}$ is the decennial change in the share of education group E, $EDUSH^E_{j,o,t} = \left(\frac{L^E}{L^L+L^M+L^H}\right)_{j,o,t}$, on the total of immigrants from origin-country o in destination j between decades t and $t+1$. We consider low, middle and highly educated workers, i.e. $E \in \{L, M, H\}$. $\Delta X^E_{o,t}$ represents the change in the relative labour market conditions of education group E in the origin countries and $\Delta EDUSH^E_{o,t}$ is the change in the education share in origin countries. This specification has the advantage that the coefficients represent now the percentage point change of the education share of immigrants from origin country o in destination j of a one unit change of each regressor. While β^E_3 should be positive for all education groups, we expect that $\beta^H_1, \beta^L_1 > 0$ and $\beta^M_1 < 0$ according to the reasoning above. However, Michaels et al. (2014) note that the effect on the poorly educated group may be ambiguous.

We finish this section with a note on our proxy for relative demand shifts in the destinations j. Certainly, employing the initial routine share of employment as suggested by Autor and Dorn (2013) is not the only way to proxy for local relative demand shifts. Alternative ways include exploiting local trade shocks as in Autor et al. (2013a,b), or more generally, exploiting a region's initial industrial structure in combination with exogenous national employment shifts as suggested by Bartik (1991).[16] We stick to the routine share as this illustrates one particular channel affecting the skill composition of immigrants and investigate alternative channels in the robustness part of section 3.4.

3.3 Data, Measurement and Stylized Facts

In this section, we first provide summary information on how we combine data from the Swiss census and from origin countries, with further details deferred to the data appendix 3.B. Secondly, we outline how we measure relative demand shifts at the level of local labour markets. Thirdly, we present a set of stylised facts on the polarisation of the Swiss labour market which underscores the relevance of using the routine intensity of local labour markets as proxies for relative demand shifts for skills.

[16]Recent applications of what is commonly known as Bartik instruments include Notowidigdo (2011) or education specific as Peri et al. (2014) and Moretti (2004).

3.3.1 Data Sources and Definitions

Immigrants, Education Groups and Destinations

We use data from the Swiss Census, which constitutes a complete inventory count of the population for the years 1970, 1980, 1990, 2000. For the years 2010 to 2012, we use the annually conducted *structural survey* which replaced the Census. This survey contains a representative, 3% sample of the total population.[17] As we break down this data into commuting zone, origin country and education group cells, we pooled the structural surveys from 2010 to 2012 to gain more accuracy. Our sample consists of individuals of age 16 to 64 who report nonzero working hours. Labour supply is measured in full time equivalents based on weekly hours worked. Workers in the *structural surveys* were weighted using the official sampling weights.

We classify individuals into *natives* and *recent immigrants* according to their country of birth. Recent immigrants are non-Swiss born, having arrived in Switzerland not more then 5 years before the Census wave.[18] Among recent immigrants, we distinguish workers from 30 different origin countries based on their country of residence 5 years ago.[19] As the Swiss Census does not distinguish different places of origin for immigrants from Ex-Yugoslavia and the former Czechoslovakia prior to the 2010, we aggregate immigrants from all available countries of former Yugoslavia and aggregate immigrants from the Czech Republic and Slovakia in the Census 2010 to 2012 waves.

Workers were classified into three education groups using the International Standard Classification of Education (ISCED) following Peri (2005). *Highly educated* workers hold a tertiary degree (ISCED 5 and 6), whereas *middle educated workers* hold a degree from a secondary school (ISCED 3 and 4). *Poorly educated* workers are those with compulsory education only or less (ISCED 0, 1 and 2).

For our *destinations*, we make use of a time-consistent definition of local labour markets provided by the Swiss Statistical Office which has been widely used in the applied

[17] This new "census" takes place annually with the 31 December as the day of reference (see Swiss Federal Statistical Office, 2011 for more). Due to this major change and some other redefinitions of variables (see the online data appendix for details), one has to compare aggregate statistics over time with some caution. Moreover, for some of the variables there were many missing observations which could not be included in the analysis. We compared many of the results with other datasets such as the Swiss Earnings Structure Survey (SESS) or the Swiss Labour Force Survey (SAKE) and therefore are confident that our dataset yields representative results.

[18] In Censuses 2010 to 2012, the information on the year of arrival is missing in some entries. In this case, we classified foreign-born residents as recent immigrants if they had a short-term residency permit (B, L) and as earlier immigrant if they had a long-term permit (C).

[19] Using the last residency country reflects more closely the immigration decision in the sense of Grogger and Hanson (2011) compared just using the country of birth as origin. However, the correlation between the two classification of origin is very high in our data.

literature.[20] The Swiss Statistical Office segments Swiss municipalities into 106 commuting zones (CZs) which are characterised by strong commuting-ties within CZs and weaker commuting ties across CZs. CZs represent internally homogenous labour markets with an orientation towards a centre and represent the closest approximation of functionally independent local labour markets employed in the theoretical model of Autor and Dorn (2013). An additional advantage of this definition is that these CZs may be aggregated into 16 larger labour markets to check robustness of our analysis.

Using these definitions, we collapse our dataset into year, CZ, country group and education group cells for recent immigrants. One not negligible issue is the presence of zero or missing bilateral migration stocks. As Grogger and Hanson (2011) point out, based on the law of large numbers, theory would predict all bilateral stocks to be positive, though some might be very small. Yet, zero migration stocks might occur in finite populations, if bilateral migration probabilities are very small. We deal with this by setting all empty cells to zero in the years 1970 to 2000, since for those years, we have a full inventory of the residency population in Switzerland. If however for any CZ observations were missing for all educations groups, the calculation of education shares is mathematically not defined and, hence, such a CZ was treated as a missing observation. Since we cannot rely on a full inventory count for $t \geq 2010$, we treated all empty cells as missing. In section 3.4.4, we demonstrate that our results are robust to alternative treatments of empty migration cells.

Origin Country Information

We complement the Swiss Census data with data of origin countries from various sources to control for origin country push drivers in our baseline sorting regression equation. We calculate *the shares of education groups* in origin countries using data from Barro and Lee (2013). Barro and Lee (2013) report the percentage of the population with some type of educational attainment (completed and uncompleted) for the population aged 15 or older. We define 'no schooling attainment' and 'primary schooling attainment' as *poorly educated*, 'secondary schooling attainment' as *middle educated* and 'tertiary schooling attainment' schooling attainment as *highly educated*.[21]

We use data from the Luxembourg Income Study (LIS) 'Key Figures' (Version 3) for *income based Gini coefficients* and to construct *education specific wage measures* by origin country as follows. Since a number of comparison issues arise when working with

[20]See Schuler et al. (2005) for a detailed description and Favre et al. (2013) for a recent analysis using commuting zones as local labour markets.

[21]We use the population weighted means from Albania, Serbia, Croatia and Slovenia to calculate the education measure for 'Ex-Yugoslavia' and of the Czech Republic and Slovakia for measure of 'Czechoslovakia'.

educational attainment information directly using the LIS, we follow Grogger and Hanson (2011) and use the quantiles of a country's earnings distribution to gauge wages of different education groups. The LIS provides information on the ratio of the the 90th percentile to the 10th percentile and of the 90th percentile to the median for various countries earnings distributions in different years.[22] We approximate median income by origin country with GDP per capita from Heston et al. (2011) and use the ratios from the LIS to gauge incomes for the 90th and 10th percentile. We use the median wage as our wage measure for middle educated workers, and the 90th and 10th percentile as a wage measure for highly and low educated, respectively.[23]

Table A.1 presents summary statistics of all variables used and table A.2 presents the list of origin countries ranked by the number of immigrants in Swiss local labour markets.

3.3.2 Measuring Routine Intensities

A crucial ingredient in our analysis is a measure of routine task intensity as a proxy for relative demand shifts. We measure the routine task specialisation of a CZ using their occupational composition of employment. To this end, we merge job task requirements from the Dictionary of Occupational Titles (DOT 1977) to ISCO-88 occupations available in the Swiss Census in order to measure the routine, abstract and manual task content of each occupation.[24] We thereby assume that the skill requirement of occupations in Switzerland is similar to their U.S. counterparts.[25] The DOT provides an assessment of the skill requirements of each U.S. Census occupation assigned by experts on a zero to ten scale. Thus, each occupation comprises multiple task requirements at different levels

[22]We linearly interpolate the ratios in missing years between available waves and extrapolate trends up to 10 years to minimise the loss of observations.

[23]In the LIS only data from Slovenia is available for the group of Ex-Yugoslavian countries. As the absolute wage differences by education group might be important as Grogger and Hanson, 2011 point out, we calculated the weighted means of GDP per capita of Albania, Serbia, Croatia and Slovenia for Ex-Yugoslavian countries as the median income measure and used then the percentile ratios of Slovenia to gauge the wages by education groups in all Ex-Yugoslavian countries.

[24]Autor and Dorn (2013) provide a measure for routine, abstract and manual task content for US 2000 census occupations (occ2000) from the Dictionary of Occupational Titles 1977. These three task aggregates were collapsed from originally five task measures first used in Autor et al. (2003). We use a crosswalk from the US National Crosswalk Service Center (NCSC) to match these variables to the International Standard Classification of Occupations (ISCO-88) available in the Swiss Census. See online data appendix for more details.

[25]Knowing that both countries lie at the world technology frontier (e.g. Caselli and Coleman, 2006) we believe this assumption to be reasonably satisfied for most occupations. In a similar way, Goos et al. (2009) use task requirement information from the Occupational Information Network (O*NET), the successor of the DOT, to build a measure of routine intensity for ISCO-88 occupations in different European countries. We use task measures from the DOT as the information on the task content of occupations should be predetermined and we use 1980 as the first year of our baseline analysis. We checked the robustness of results using instead the task measures from the O*NET data base.

of intensity.[26] Following Autor and Dorn (2013) we combine the three task measures to create a summary measure of routine-intensity RTI by occupation:

$$RTI_k = \ln\left(T^R_{k,1980}\right) - \ln\left(T^M_{k,1980}\right) - \ln\left(T^A_{k,1980}\right) \tag{3.8}$$

where $T^R_{k,1980}$, $T^M_{k,1980}$ and $T^A_{k,1980}$ are the routine, manual and abstract task inputs in each occupation k in 1970.[27] This measure is increasing in the importance of routine tasks in each occupation and declining in the importance of manual and abstract tasks.

Table 3.1 reports the share of education groups, the task scores from the DOT (standardized to have mean zero and standard deviation one) and the routine intensity as defined by Equation (3.8) for each 1-digit ISCO group in the year 1980.[28] Occupation groups are ranked in an descending order by their mean wage in 1991.[29] This table shows that the three highest paid occupations (Managers, Professionals and Technicians) all have a relatively high abstract task requirement whereas their manual and routine scores are comparatively low. Workers in these occupations are to a large extend highly educated compared to other occupations. Occupations in the middle of the wage distribution (Clerks, Craftsmen and Operators) show relatively low abstract but high routine task requirements. These occupations typically employ workers with a middle level of education.[30] Service occupations and elementary occupations at the bottom of the wage distribution have low average education levels and low levels of routine task inputs in combination of rather high scores of the manual task. Table A.3 shows the standardised task requirement score, averaged over all workers for each education group. Unsurprisingly, this table confirms that workers with a middle education level work in occupations with the highest routine task content, whereas low educated workers work in manual jobs and high educated workers in occupations with a high abstract task content. Essentially, this

[26]Autor and Dorn (2013) show, for instance, that cognitive abstract skills are most important in professional and managerial occupations, whereas manual skills are most important in in-person service occupations such as cleaning and health care. Routine task input is most dominant either in clerical occupations (for routine-cognitive tasks) or in machine operator or assembly occupations (for routine-manual tasks).

[27]Each task is measured on a one to ten scale, with ten meaning that the task is most heavily used in this occupation.

[28]We experimented with slightly different classification systems. Acemoglu and Autor (2011) and Autor (2010) for instance suggest allocating part of ISCO88 group 9 (elementary occupations) to ISCO88 group 8 (operators) while allocating the remaining occupations to ISCO88 group 5 (service occupations) according the the task content of these ISCO88 subgroups. For the sake of clarity, we decided to follow Goos et al. (2009) and report all results for ISCO88 main groups. Taking the classification of Acemoglu and Autor (2011) does not significantly alter the results. See the discussion in online data appendix.

[29]No wage data prior to that date for these occupations. For wages, we used the Swiss Labour Force Survey (SAKE).

[30]Note that plant and machine operators have a relatively high share of low educated workers combined with a relatively high manual task input. The manual task requirement of this occupations group, however, is mainly of a routine-manual type which is also subject to automatisation.

finding confirms what Michaels et al. (2014) have found for several other OECD countries.

Table 3.1: Task Content and Education Group Shares of ISCO Main Occupations

	Education Group Shares			Task Content			
ISCO Main Groups	high	middle	low	abstract	routine	manual	*RTI*
Managers	0.28	0.52	0.20	1.93	-1.12	-0.61	-0.89
Professionals	0.76	0.20	0.04	1.77	-0.60	-0.13	-0.70
Technicians	0.17	0.68	0.15	0.34	-0.11	-0.47	0.18
Clerks	0.06	0.65	0.29	-0.39	0.86	-0.88	1.18
Craft and Related Trades	0.04	0.54	0.42	-0.40	0.87	0.47	0.00
Plant and Machine Operators	0.01	0.35	0.64	-0.69	-0.40	1.05	-0.34
Service and Sales	0.04	0.49	0.47	-0.54	-1.07	-0.15	-0.23
Elementary Occupations	0.05	0.31	0.64	-1.06	-0.43	0.56	0.17

Notes: Occupation groups are ranked by their main log wage in using data from the Swiss Labour Force Survey (1991-1993 pooled). Agricultural workers are omitted. Task measures taken from DOT as described in Section 3.3. Routine intensity (RTI) calculated as in equation (3.8). Task measures and RTI scores are first standardised then and averaged over all workers in an occupation group using employment weights from the 1980 Swiss Census.

To measure routine intensity at the level of local labour markets, we proceed in the following way. First, we identify the set of occupations in the top employment-weighted third of routine task-intensity in 1970.[31] These occupations are subsequently referred to as routine-intensive occupations. Next, we calculate for each commuting zone j the employment share of these routine-intensive occupations, $RSH_{j,t}$ as:

$$RSH_{j,t} = \left(\sum_{k=1}^{K} L_{jkt} * 1[RTI_k > RTI^{P66}] \right) \left(\sum_{k=1}^{K} L_{jkt} \right)^{-1} \tag{3.9}$$

where L_{jkt} is the employment in occupation k in commuting zone j and decade t. $1[.]$ is an indicator function taking a value of one if occupation k is in the top employment-weighted third of routine task-intensity in 1970.

3.3.3 Job and Wage Polarisation in Switzerland

In our empirical analysis, we use the employment specialisation in routine occupations of a local labour market as a proxy for shifts to the relative demand for workers with different educational backgrounds. A large literature has documented the association between initial specialisation in routine employment an the subsequent adoption of computer capital polarising the wage and employment distribution for most developed countries (Autor and Dorn, 2013; Goos et al., 2009; Michaels et al., 2014). Dustmann et al. (2009) point out, however, that there are potentially important cross-country differences, e.g. due to

[31] We performed robustness checks using alternative cut-off levels for defining routine-intensity. None of our results crucially hinged on this choice.

institutions, in how these technology shocks affect the occupational employment and wage distribution in detail. For Switzerland, these trends have not been documented satisfactorily over a long time period and using detailed information on occupations and tasks in accordance with the most recent academic literature.[32] In this subsection we document, first, that job and wage polarisation are also pervasive features of long-run trends in the Swiss labour market affecting both natives and recent immigrants on the national level. Second, we show that job polarisation also affect the skill composition in local labour markets depending on their initial specialisation in routine occupations.

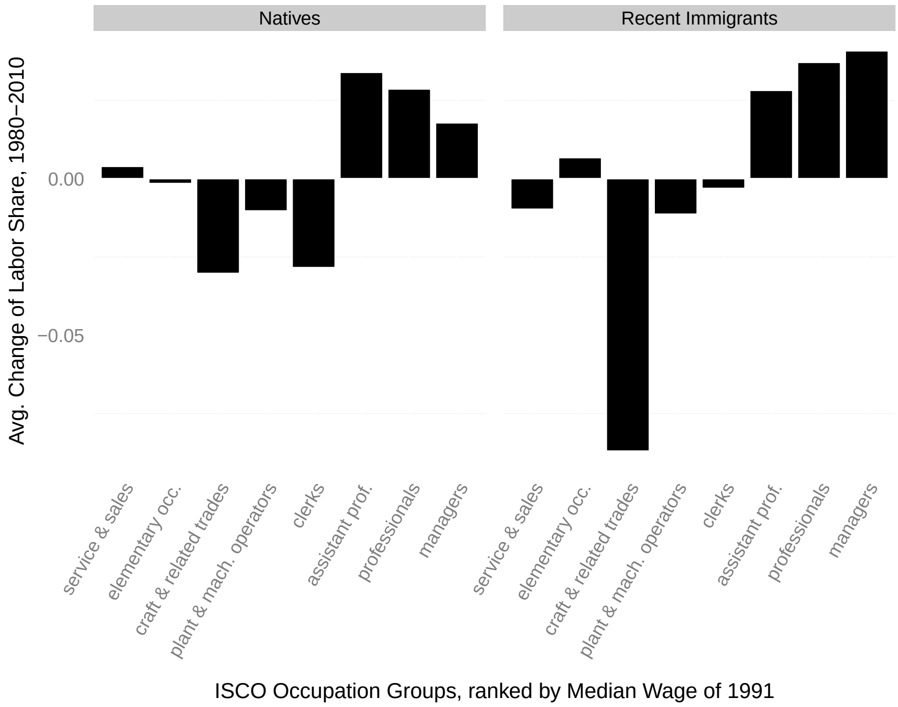
Job and Wage Polarisation on the National Level

Figure 3.2 shows the changes of our 1-digit ISCO groups, where we excluded occupations related to agriculture, separately for natives and recent immigrants (table A.4 provides details and figure A.1 shows the results for the total labour force). Occupations in each pane of figure 3.2 are ranked by the median wage from the pooled Swiss Labour Force Surveys (SLFS) 1991 through 1993.[33] As can be seen, natives as well as recent immigrants are subject to polarisation. In fact, for recent immigrants the patterns seem to be even more pronounced than for natives. For example, the employment share of managers (ISCO 1) almost doubled on average for recent immigrants in every decade, growing from 2.7% in 1980 to almost 15% in 2010 whereas for native workers it grew from about 6.7% to to 11.4%. On the other hand, the share of craftsmen (ISCO 7) fell from over 42% in 1980 to less than 15% in 2010 among recent immigrants. For natives, it changed from 23% to about 14%. Finally, the fraction of poorly paid workers in service and elementary occupations (ISCO 5 and 9) stayed at somewhat more than 20% among recent immigrants, and around 16% for natives throughout our time horizon (one reason why the pattern for recent immigrants is stronger may be that the group resembles closer a flow of workers, rather than a stock as in the case of natives).

[32] Oesch and Menés (2011) compare job polarisation in Switzerland, the UK, Spain and Germany. For Switzerland, the rely on a relatively small sample from the Swiss Labour Force Survey and a relatively short time span between 1991 and 2008, i.e. when computerisation was already well underway. Splitting the employment distribution into earnings quintiles, they find employment growth only at the top of the earnings distribution. Favre et al. (2012) and Müller et al. (2013) an increase in wage-inequality at the top of the wage distribution relative to the middle but do not rely on occupations for their analysis as we do here. Consequently, they do find very different results for wage changes at the bottom.

[33] Appropriate wages for ISCO categories are not available prior to 1991, the first year of the SLFS. We pool the SLFS of three years in order to get reasonably large numbers of observations for each two-digit ISCO category.

Figure 3.2: Average Decennial Change in Employment Shares of Occupation Groups by Nationality, 1980 - 2010



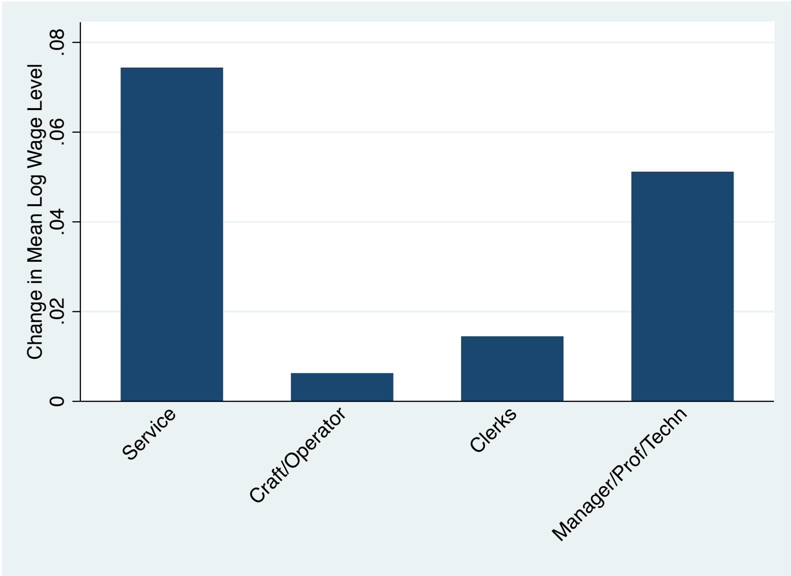
Notes: Occupation groups are ranked by their Median Wage from the Swiss Labour Force Survey (1991-1993 pooled). Employment data from the Swiss census 1980 - 2010.

According to the routinization argument, we would expect a similar picture for occupational wages: Relatively strong growth for abstract and service occupations and more modest growth for routine occupations. Figure 3.3 plots the change in the mean log hourly wages by occupation groups. As we have to rely on the small sample size of the SLFS, we aggregated ISCO main occupations according to their task content in four groups, non-routine occupations (service), routine manual occupations (craft workers & operators), routine cognitive occupations (clerks) and non-routine abstract occupations (managers, professionals and technicians). We ranked those groups again by their mean log wage in 1991.[34] Evidently, wage growth is most pronounced at the bottom, with gains of about 0.07 log points in real terms for manual service workers, and at the top; Wages of abstract workers increased by about .05 log points. In contrast, wage gains of craftsmen and operators (employed in routine manual jobs) and clerks (representing routine cognitive workers) were considerably more modest (0.005 and 0.015 log points in real terms, respectively).

To sum up, paralleling trends in most other OECD countries, we find that in Switzer-

[34]Cf. the notes of the figure. As the SLFS samples are relatively small, we aggregated ISCO 5 and 9 into service occupations, ISCO 7 and 8 into craft/operators, ISCO 4 as clerks and ISCO 1 to 3 into managers/professionals/technicians.

Figure 3.3: Change in Mean Log Hourly (Real) Wages of Occupation Groups, 1991 - 2011



Notes: Change in mean log hourly wages by broad occupation groups between 1991 and 2011. Service occupations is the aggregate of ISCO 5 and ISCO 9 occupations, Craft/Operators is the aggregate of ISCO 7 and ISCO 8 occupations, Clerks is ISCO group 4 and Manager/Prof/Techn is the aggregate of ISCO 1 to 3 occupations. The years 1991 through 1993 and 2009 through 2011 are pooled to gain precision. Swiss Labour Force Survey data.

land, routine occupations show decreasing employment shares with losses most pronounced in routine manual occupations (operators and craft) but also in routine cognitive jobs (clerks). On the other hand, abstract occupations at the top of the wage distribution (managers, professionals and technicians) as well as employment in low-paid (service and elementary) occupations show increasing employment shares. In addition to this, we find that job polarization seems to be amplified among the foreign-born labour force.

Relative Demand Shifts in Local Labour Markets

Having found clear trends of job and wage polarisation on the national aggregate, we inspect whether the Swiss data bear out the hypothesis of Autor and Dorn (2013) on the local level. This hypothesis posits that a CZ with a stronger initial routine intensity experiences greater adoption of automation capital. Accordingly, these regions should have experienced a greater relative demand shift and, thus, greater increases in the share of highly educated workers. Using geographical variation in our data, figure 3.4 provides graphical evidence on this prediction. Panel A relates the routine share of a commuting zone (CZ) in 1980 (as defined in Equation 3.9) to the change of the share of highly educated workers from 1980 to 2010. The variation in the local routine intensity, $RSH_{j,1980}$, is substantial: For instance, only roughly 15% of the workforce was employed in routine-intensive jobs in Schwarzwasser, whereas this share was almost 50% in La Chaux-de-Fonds. Intuitively, routine-intensity is highly correlated with either routine-manual work in industrial areas or routine-cognitive work in regions with a large domination of the service sector in the 1980s. Urbanised regions such as the service-intensive Zurich and Geneva (financial sector) or industrial Basel (chemical industry) as well as rather rural CZs such as Glarner Hinterland and Glarner Unterland (textile industry) or the peripheral La Chaux-de-Fonds and Jura (watchmaker industry) lie at the right extreme of the spectrum. On the other extreme, we find rural areas which were more influenced by tourism industries. The figure shows a clear positive relation between a CZ's initial routine intensity and the subsequent relative growth of high skill labour; CZ with a one percentage point higher routine share in 1980 are expected to experience a 0.466 percentage point higher increase in the share of highly educated workers. For instance, the simple OLS prediction (without controls) would predict that Zurich, with an initial routine intensity of 42%, would experience a 12 percentage points higher increase in highly skilled labour ($0.43 \times 0.3 \times 100$) compared to Schwarzwasser, whose routine share was only 12% in 1980.[35]

In contrast, initial routine intensity is negatively related to the subsequent change in the share of middle educated workers as Panel B of figure 3.4 shows. Finally, Panel C shows a positive relationship between the $RSH_{j,1980}$ and the change of the share of poorly educated workers. As mean growth of the share of poorly skilled workers is negative and positive in the case of middle skilled workers, this might seem puzzling at first sight. However, this reflects the international trend of skill upgrading: If the supply of skills becomes generally more biased towards highly skilled workers, this growth may offset relative demand shifts originating from technical change (see also Michaels et al., 2014). Nevertheless, Panel B and C suggest that regions with larger routine specialisation experience stronger (weaker) demand for poorly (middle) educated workers than regions with a small routine input in 1980.

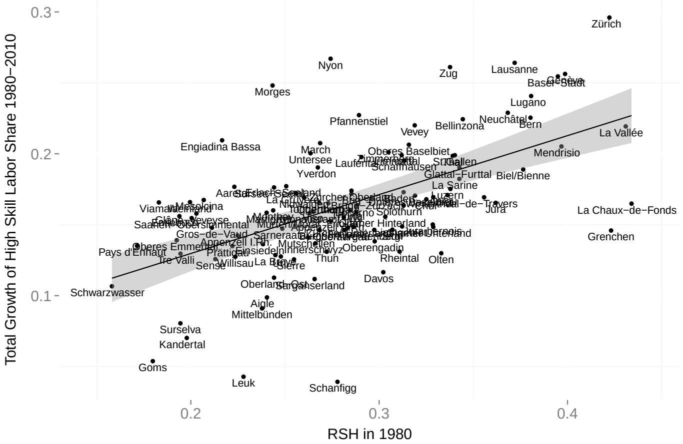
In what follows, we document that the polarising skill demand offers a key explanation for the skill composition of new immigrants.

[35] The OLS regression lines depicted in the figures 3.4 are all unweighted. If we weight the observations by their total labour force in 1980, the results become even stronger.

Figure 3.4: Change in the Share of Highly, Middle and Low Educated Workers in Commuting Zones, 1980 - 2010

A. Change in the share of highly educated workers

$$\Delta EDUSH^{H}_{j,1980-2010} = 0.005 + 0.385 \times RSH_{j,1980} + \epsilon_{j,\tau} \quad R^2 = 0.296 \quad n = 106$$

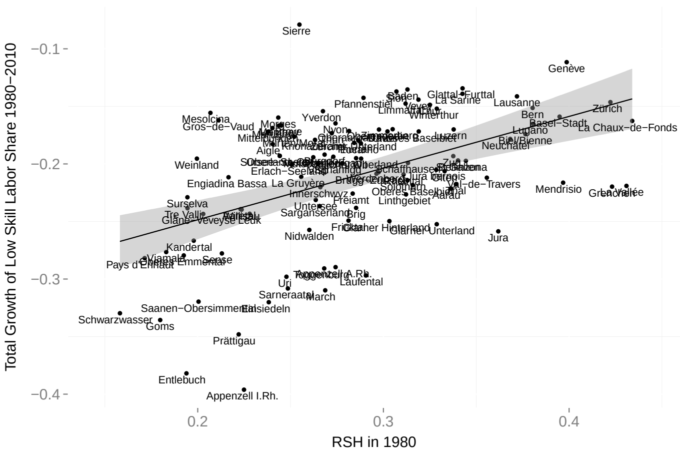


B. Change in the share of middle educated workers

$$\Delta EDUSH^{M}_{j,1970-2010} = 0.283 - 0.857 \times RSH_{j,1980} + \epsilon_{j,\tau} \quad R^2 = 0.382 \quad n = 106$$

C. Change in the share of low educated workers

$$\Delta EDUSH^{L}_{j,1970-2010} = -0.335 + 0.472 \times RSH_{j,1980} + \epsilon_{j,\tau} \quad R^2 = 0.237 \quad n = 106$$



Notes: Scatterplot of the change in the share of highly, middle or low educated native workers (Panel A, B, C respectively) between 1980 and 2010 on the share of routine occupations for each of the 106 commuting zones in 1980. Unweighted OLS prediction with confidence intervals. Swiss Census 1980 and 2010.

3.4 Results

3.4.1 Determinants of the Skill Composition of Newly Arriving Immigrants

OLS Estimates

While the last section provided some preliminary, graphical evidence about the effect of routinization on skill demand, this section takes our empirical counterpart of the sorting equation, Equation (3.7), directly to the data. Table 3.2 reports the results of our baseline specifications. The dependent variable in Panel A is the decennial change in the share of highly skilled recent immigrant workers. Panel B shows the results for the middle skilled and Panel C for the poorly skilled share among recent immigrants workers. We confirm this conjecture in table A.6 in the appendix which shows the regression results for equations (3.5) and (3.6) - the explicit empirical counterparts of Grogger and Hanson (2011)'s sorting equations. In all regressions, cells are weighted using the total number of recent immigrants from origin country o in destination j at the beginning of the decade as weight.[36] The first three columns consist of OLS regressions whereas the remaining columns represent 2SLS regressions to address potential endogeneity concerns (see below).

Column 1 of table 3.2 includes only our proxy for relative demand shifts, RSH and fixed effects for cantons, decades and origin countries. Abstracting from push and pull factors other than constant effects over time, country and destinations, the coefficient indicates that a region with a one percentage point higher routine input in 1980 would subsequently experience an about 0.19 percentage point stronger growth of its high-skill employment share in every decade among recent immigrants. On the other hand, we find a negative relationship among middle educated and a positive, though not significant, coefficient in case of poorly educated immigrants. Considering the large variability of the RSH in 1980 (figure 3.4), this would result in substantial differences in the skill composition of CZs after a few decades.

In column 2, we add controls for the changes in the relative skill supply and remuneration in origin countries. Note that this substantially reduced the number of observations, as we do not have both of these measures for all origin countries and decades. For changes in skill supply measured as changes to education stocks in origin countries reported by Barro and Lee (2013), we find that a change of the highly skilled labour share abroad translates almost one to one into a higher educated immigrating labour force as posited by the model of Grogger and Hanson (2011) (see equation (3.4)). The same holds true for

[36]These weight reflect the importance of each cell for the aggregate picture and also account for the likely inaccuracy of very small cells. We explore different weighting schemes in section 3.4.4.

middle skill employees whereas the estimations point to a slightly lower reaction in the case of low-skill migrants. The latter might indicate a smaller labour market mobility in case of low-skill compared to high-skill workers, a fact which is well-documented in the literature (see, for example, Bartel, 1989 or Malamud and Wozniak, 2012). The effects for relative demand shifts in origin countries, measured in changes to wage differences of education groups as suggested by Grogger and Hanson (2011), are all estimated to be close to zero and sometimes have the wrong sign. Although they have the right sign for highly educated immigrant workers, we would have expected a positive sign for low educated workers, a positive sign for $\Delta\left(w^{H}-w^{M}\right)_{o,\tau}$ and a negative sign for $\Delta\left(w^{M}-w^{L}\right)_{o,\tau}$ in the case of middle educate workers. These findings seem to suggest that that relative demand shifts in origin countries are less important once we account for demand shifts in destinations and shifts to education supply. The minor importance of push drivers, especially income levels in origin countries, has also been acknowledged by Mayda (2010) for the general magnitude of migration flows.

Column 3 includes the change of per capita GDP in origin countries relative to the change of Swiss per capita GDP, in order to control for other omitted push and pull variables which influence the labour markets, in particular the business cycle. Higher GDP growth abroad tends to decrease the share of poorly skilled migrants whereas it has a smaller or insignificant effect on middle and highly skilled migrants.

2SLS Estimates

One potential concern for the identification of our demand effect in destinations are cyclical factors affecting a commuting zone's industrial composition and hence its routine intensity in the short-run and at the same time influencing the skill composition of immigrants. If this were the case, using the routine intensity at the beginning of the decade would lead to a biased estimate of the demand effect. This point has also been highlighted by Autor and Dorn (2013) from whom we borrow the identification strategy of relative demand shifts. To make an example in our context, note that a couple of very routine intensive commuting zones, like Grenchen, La-Chaux-de-Fonds, La Vallee or Jura (see figures 3.4), were all dominated by the Swiss watch making industry. Task inputs in this industry were highly routine intensive in the 1980s. During the 1970s and 1980s, Swiss watchmakers saw their global market share plummeting due to international competition. This may have released a large share of such a region's workforce out of routine jobs into jobs with a more abstract or service task content. To the degree this cyclical spike to final demand for watches also affected the subsequent skill demand in these regions, it confounds our identification strategy.

To purge our main regressor from this kind of variation, we follow Autor and Dorn

(2013) and use an imputed measure for the routine share, $\widetilde{RSH}_j$, as an instrument. More specifically, by predicting the local routine intensity using the countrywide routine share of industries and the local industry composition, we obtain an exogenous measure of local changes to labour demand:

$$\widetilde{RSH}_j = \sum_i L_{i,j,1970}^{Natives} \times RSH_{i,-j,1970}^{Natives} \tag{3.10}$$

$L_{i,j,1970}^{Natives}$ represents native employment in industry i as a share on total native employment in CZ j in 1970. $RSH_{i,-j,1970}^{Natives}$ represents the routine share of native workers in industry i in all CZs except j at the start of our time span, 1970.[37] Since we use the 1970 census to calculate our IV and start the sample for the regressions in 1980, our instrument should be uncorrelated to cyclical spikes in, for example, final demand. By using only *native* employment for the calculation of the IV, we gain additional confidence that the variation of our instrument is exogenous in case of the regressions for recent immigrants.[38]

Appendix table A.5 reports the first stage estimates for this instrumental variable strategy using only fixed effects as controls. Unsurprisingly, these first stage results are very similar across education groups, which is why we present the estimates for the highly educated in the second stage only. Column 1 corresponds to the pooled regression with the stacked routine intensity at the beginning of each decade from 1980 to 2010. Columns 2 to 4 show first stage estimates, separately by decade. The declining magnitude of the coefficients illustrates how the predictive power of initial routine intensity in 1970 declines over time which has also been noted by Autor and Dorn (2013).

The last five columns in table 3.2 show the resulting instrumental variable estimates. Column 4 corresponds to the OLS specification in column 1 and, again, confirms our expectation that routinization has a positive impact on the demand for highly educated immigrants. Compared to that, on the other hand, we find again an adverse effect for the demand for middle and poorly skilled migrants. Column 5 again shows the results for our full baseline specification, given by equation (3.7) and column 6 adds relative GDP per capita growth to proxy for other changes on the origin country labour market. All coefficients for our demand shifter, RSH, and the education supply measure prove stable and highly significant.

As the change in the wage differences induced from income percentile ranks in origin

[37]More precisely, we take native workers employed by industry i in routine-intensive occupations as a share on total native employment in industry i.

[38]We use only the native employment to calculate the routine intensity in 1970 to address the potential problem that immigrant could be clustered in routine occupations. This could result in the problem that high routine employment share in a region actually reflects high past immigrant employment which could drive future immigrant inflows through ethnic networks (Card, 2001). We ran regressions with the routine intensity inducing and not inducing past immigrants without any impact on the results.

countries might be measured with some error, we replace it with the Gini index, similar to other studies (Clark et al., 2007; Mayda, 2010). Again, changes to the relative inequality in origin countries seem to be of minor importance for the change of the skill composition of immigrants once relative demand in destinations and education supply is accounted for.

Finally, to control for still other omitted push variables, or for potential deficiencies of our foreign wage measures, column 7 adds origin-country fixed effects interacted with time dummies. Reassuringly, our estimates for the RSH coefficient prove to be robust even to this very demanding specification. Furthermore, the F-Statistic in case of all 2SLS estimates are well above the conventional threshold of 10 which makes us confident that our IV strategy works generally well (Stock et al., 2002).

Table 3.2: Determinants of the Change in Education Group Shares of Recent Immigrants, 1980 - 2010, OLS and 2SLS Estimates

	OLS			2SLS				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Dependent Variable: Change of High Skill Labour Share								
$RSH_{j,t}$	0.188	0.212	0.193	0.341	0.390	0.369	0.370	0.311
	[0.054]***	[0.078]***	[0.077]**	[0.110]***	[0.099]***	[0.100]***	[0.100]***	[0.092]***
$\Delta EDUSH^{H}_{o,\tau}$		1.039	0.813		1.024	0.799	0.845	
		[0.343]***	[0.155]***		[0.335]***	[0.142]***	[0.180]***	
$\Delta\left(w^{H}-w^{M}\right)_{o,\tau}$		-8.49e-07	-3.73e-06		-6.91e-07	-3.56e-06		
		[0.000]	[0.000]**		[0.000]	[0.000]**		
$\Delta GDPPC_{o,\tau}$			0.0153			0.0152	0.0136	
			[0.003]***			[0.003]***	[0.003]***	
$\Delta GINI_{o,\tau}$							-0.145	
							[0.090]	
R-squared	0.003	0.043	0.104	0.001	0.040	0.101	0.100	0.248
F-Stats				49.69	48.26	48.09	47.97	48.80
B. Dependent Variable: Change of Middle Skill Labour Share								
$RSH_{j,t}$	-0.262	-0.244	-0.247	-0.294	-0.291	-0.293	-0.296	-0.280
	[0.102]***	[0.106]**	[0.108]**	[0.116]**	[0.110]***	[0.109]***	[0.109]***	[0.104]***
$\Delta EDUSH^{M}_{o,\tau}$		1.003	1.014		1.001	1.011	0.913	
		[0.260]***	[0.263]***		[0.261]***	[0.264]***	[0.243]***	
$\Delta\left(w^{H}-w^{M}\right)_{o,\tau}$		-3.86e-06	-3.74e-06		-3.88e-06	-3.76e-06		
		[0.000]	[0.000]		[0.000]	[0.000]		
$\Delta\left(w^{M}-w^{L}\right)_{o,\tau}$		2.24e-05	2.06e-05		2.23e-05	2.05e-05		
		[0.000]***	[0.000]**		[0.000]***	[0.000]**		
$\Delta GDPPC_{o,\tau}$			0.00179			0.00182	0.00449	
			[0.002]			[0.002]	[0.002]***	
$\Delta GINI_{o,\tau}$							0.108	
							[0.069]	
R-squared	0.007	0.081	0.082	0.007	0.081	0.082	0.074	0.167
F-Stats				49.69	48.09	47.87	47.81	48.80
C. Dependent Variable: Change of Low Skill Labour Share								
$RSH_{j,t}$	0.0738	0.0232	0.0600	-0.0477	-0.103	-0.0723	-0.0733	-0.0319
	[0.108]	[0.116]	[0.116]	[0.099]	[0.104]	[0.097]	[0.095]	[0.092]
$\Delta EDUSH^{L}_{o,\tau}$		0.623	0.669		0.624	0.670	0.667	
		[0.216]***	[0.127]***		[0.215]***	[0.121]***	[0.114]***	
$\Delta\left(w^{M}-w^{L}\right)_{o,\tau}$		-1.34e-05	1.91e-06		-1.37e-05	1.55e-06		
		[0.000]	[0.000]		[0.000]	[0.000]		
$\Delta GDPPC_{o,\tau}$			-0.0186			-0.0185	-0.0182	
			[0.002]***			[0.002]***	[0.001]***	
$\Delta GINI_{o,\tau}$							0.0117	
							[0.063]	
R-squared	0.001	0.068	0.165	-0.001	0.067	0.163	0.163	0.206
F-Stats				49.69	48.08	47.82	47.79	48.80
Observations	4,144	2,987	2,987	4,144	2,987	2,987	2,987	4,144
Decade × Orig. Country FE	No	No	No	No	No	No	No	Yes

Notes: ***, **, *, denote statistical significance at the 1%, 5% and 10% level, respectively. Robust standard errors (clustered by Canton and origin country) are given in parentheses. All models include fixed effects for Cantons, origin countries and decades. Regressions are weighted using the total number of recent immigrants from origin country o in destination j at the beginning of the decade as weight. $RSH_{j,t}$ is instrumented with $\widetilde{RSH}_{j,1970}$. $\Delta EDUSH^{E}_{o,\tau}$ is the decennial change in the share of education group $E \in \{H, M, L\}$ in origin country o and decade τ. $\Delta\left(w^{M}-w^{L}\right)_{o,\tau}$ and $\Delta\left(w^{M}-w^{L}\right)_{o,\tau}$ are the decennial change in the wage differential between highly and middle and middle and low educated workers in origin country o and decade τ, respectively. $\Delta GDPPC_{o,\tau}$ and $\Delta GINI_{o,\tau}$ represent the decennial change in GDP per capita and the Gini index in origin country o and decade τ. See section 3.3.1 for a more detailed description of variables.

To summarise, our results prove to be very robust and confirm the hypotheses posited by selection model of Grogger and Hanson (2011) in combination with routinisation. While education supply almost affects the skill composition of recent immigrants one to one, we find that relative demand shifts in destinations are particularly important. There is a highly significant relation between the routine intensity of a CZ and the subsequent growth of the share of high skill immigrants. The opposite holds true for the share of middle skill labour. In the case of the low skill labour share on the other hand, the results for our main regressor turn out to be insignificant and close to zero. These results for highly, middle and poorly skilled workers broadly correspond to the results that Michaels et al. (2014) have found in case of the wage bill shares across OECD countries.[39]

As a check of the particular specification of our baseline regression model, we report results for equations (3.5) and (3.6) - the explicit empirical counterparts of Grogger and Hanson (2011)'s sorting equations in table A.6 in the appendix. These results are very similar to the finings presented here.

3.4.2 Robustness to Omitted Pull Factors in Destinations

Routinization may not be the only factor driving the skill composition of immigrants. In this section, we analyse the influence of ethnic networks and offshoring, as another potential driver of the relative demand for workers with different skills.

The location choices of current immigrants may be strongly influenced by the location decisions of their compatriots which have immigrated earlier (see, for example, Card, 2001 or Bartel, 1989). Hence, if for some reason, earlier immigrants settled in routine-intensive commuting zones at the beginning of our time horizon and this affected current inflows of their compatriots, the coefficient of our routine measure would be biased. We follow Cadena and Kovak (2013) and include the population share of immigrants from origin country o in destination j in 1970 in our regressions in order to measure the influence of ethnic networks. As can be seen in column 1 of table 3.3, controlling for such network effects has no effect on the estimates of the relative demand shifts and education supply. Interestingly, ethnic networks seem to play an important role in case of poorly educated workers, whereas for highly skilled individuals they have only minor effects. This finding is in-line with the results of Bartel (1989) who finds for the U.S. that more educated immigrants are less likely to be found in cities with a high proportion of a similar ethnic group.

In the recent literature on wage inequality, task offshoring or the impact of trade exposure is considered as one of the most important competing explanations for long-run

[39] However, note that our data is of comparatively low quality in case of ISCO occupation group 9 and thus, we consider the results for highly and middle educated workers to be somewhat more reliable.

changes to the relative demand for skills (Michaels et al., 2014). In particular, it could be the case that firms are actually not replacing workers by capital, but simply move routine-intensive task into countries with lower wages for routine labour. Several authors, see e.g. Autor and Dorn (2013) or Goos and Manning (2007) and the references therein, suspect that routine-intensive tasks are more offshorable than others (however, Blinder and Krueger, 2013 surprisingly find this not to be the case). As a result, regions with a more routine-intensive production would experience more offshoring and, therefore, their share of middle educated workers decreases faster. Although Autor et al. (2013b) showed that trade exposure and technology shocks are essentially uncorrelated on the geographical level In the U.S., we control for offshoring here to gain more certainty that technology adoption really drives our results. In so doing, we matched several offshorability measures to our dataset (see online data appendix for details). Column 2 in table 3.3 shows the results for the offshorability of ISCO-occupations calculated by Goos et al. (2011). Column 3 adds a measure for the offshorability of skills provided by Blinder and Krueger (2013) and column 4 adds an offshorability measure initially calculated for U.S. occupations by Autor and Dorn (2013). As may be expected, the skill offshorability measure as well as the Autor-Dorn measure indicate that middle skill labourers are more prone to offshoring than high-skill workers. More importantly, however, the coefficients for our main regressor, RSH, prove to be stable, and offshorability clearly plays a minor role. This confirms the results of Michaels et al. (2014), Autor and Dorn (2013) and Goos et al. (2011) who all find that routinization - not offshorability - is the key driver of labour market polarization.

Finally, we introduce origin-country fixed effects interacted with CZ-dummies to control for still other omitted factors on the level of destinations and origin countries (note that we already controlled for time-origin country fixed effects in column 8 of table 3.2). Reassuringly, our results also prove robust against this very demanding specification.

Table 3.3: Robustness of Determinants of the Change in Education Group Shares of Recent Immigrants to Omitted Pull Drivers: Existing Ethnic Networks and Offshoring, 1980 - 2010, OLS and 2SLS Estimates

	(1)	(2)	(3)	(4)	(5)
A. Dependent Variable: Change of High Skill Labour Share					
$RSH_{j,t}$	0.335	0.429	0.316	0.151	0.300
	[0.105]***	[0.134]***	[0.138]**	[0.068]**	[0.109]***
$\Delta EDUSH^{H}_{o,\tau}$	1.008	1.025	1.014	1.000	1.038
	[0.302]***	[0.309]***	[0.298]***	[0.302]***	[0.303]***
$IMSH_{j,o,1970}$	0.0557				
	[0.182]				
$OFFSH^{GMS}_{j,\tau}$		-0.0336			
		[0.022]			
$OFFSH^{BK}_{j,\tau}$			0.00314		
			[0.007]		
$OFFSH^{AD}_{j,\tau}$				0.0172	
				[0.008]**	
R-squared	0.040	0.043	0.041	0.052	0.153
F-Stats	49.57	53.62	46.26	83.77	40.67
B. Dependent Variable: Change of Middle Skill Labour Share					
$RSH_{j,t}$	-0.268	-0.341	-0.217	-0.228	-0.259
	[0.112]**	[0.137]**	[0.110]**	[0.122]*	[0.111]**
$\Delta EDUSH^{M}_{o,\tau}$	0.829	0.847	0.857	0.832	0.850
	[0.226]***	[0.235]***	[0.227]***	[0.224]***	[0.230]***
$IMSH_{j,o,1970}$	-0.454				
	[0.136]***				
$OFFSH^{GMS}_{j,\tau}$		0.0204			
		[0.019]			
$OFFSH^{BK}_{j,\tau}$			-0.0100		
			[0.005]*		
$OFFSH^{AD}_{j,\tau}$				-0.00528	
				[0.008]	
R-squared	0.053	0.052	0.055	0.051	0.163
F-Stats	49.60	53.68	46.12	83.84	40.71
C. Dependent Variable: Change of Low Skill Labour Share					
$RSH_{j,t}$	-0.0678	-0.0878	-0.101	0.0777	-0.0423
	[0.097]	[0.093]	[0.083]	[0.075]	[0.107]
$\Delta EDUSH^{L}_{o,\tau}$	0.781	0.781	0.795	0.785	0.804
	[0.232]***	[0.234]***	[0.235]***	[0.235]***	[0.237]***
$IMSH_{j,o,1970}$	0.404				
	[0.162]**				
$OFFSH^{GMS}_{j,\tau}$		0.0129			
		[0.013]			
$OFFSH^{BK}_{j,\tau}$			0.00710		
			[0.005]		
$OFFSH^{AD}_{j,\tau}$				-0.0120	
				[0.005]**	
R-squared	0.038	0.037	0.038	0.043	0.138
F-Stats	49.54	53.70	46.01	83.82	40.63
Observations	4,144	4,144	4,144	4,144	4,144
Canton × Orig. Country FE	No	No	No	No	Yes

Notes: ***, **, *, denote statistical significance at the 1%, 5% and 10% level, respectively. Robust standard errors (clustered by Canton and origin country) are given in parentheses. All models include fixed effects for Cantons, origin countries and decades. Regressions are weighted using the total number of recent immigrants from origin country o in destination j at the beginning of the decade as weight. $RSH_{j,t}$ is instrumented with $\widetilde{RSH}_{j,1970}$. $\Delta EDUSH^{E}_{o,\tau}$ is the decennial change in the share of education group $E \in \{H, M, L\}$ in origin country o and decade τ. $IMSH_{j,o,1970}$ is the population share of immigrants from origin country o in destination j in 1970. $OFFSH^{GMS}_{j,\tau}$, $OFFSH^{BK}_{j,\tau}$ and $OFFSH^{AD}_{j,\tau}$ represent measures of offshorability using the definitions of Goos et al. (2011), Blinder and Krueger (2013), Autor and Dorn (2013), respectively.

3.4.3 The effect of the changes in immigration policy on the skill composition of immigrants

An important but difficult question to tackle is whether and to which degree immigration policy can influence the skill composition of migrants that a country attracts. From this perspective, Switzerland's integration into the European labour market serves as an interesting policy experiment in which immigration restrictions for newly arriving immigrant from EU countries were abolished while immigration restrictions for other countries were kept in place. In this subsection, we show how we can incorporate policy changes into our framework to analyse the effect of liberalisation on the skill composition of immigrants. We first give some additional background information on the changes to immigration policy in Switzerland since the 1980s.

Swiss Immigration Policy Between 1980 to 2010

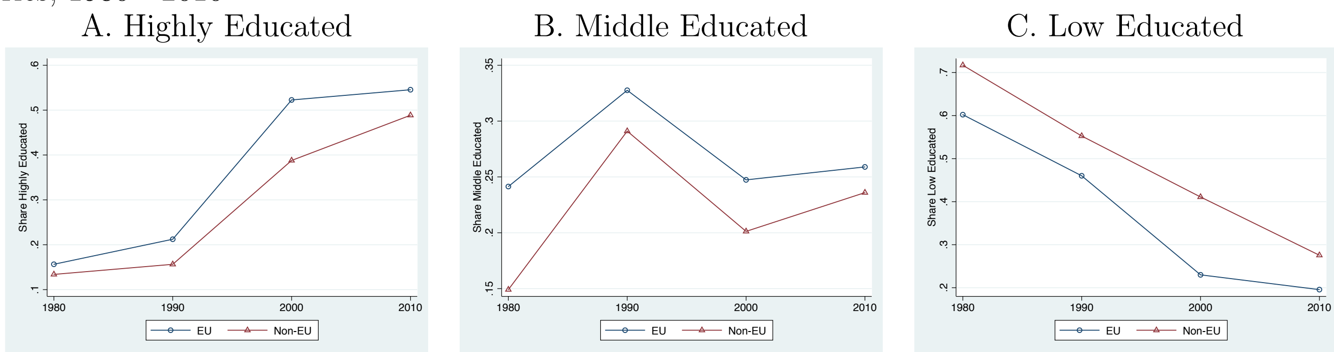
Swiss immigration policy throughout the 1980s was dominated by the desire to find a more balanced approach to govern immigration after several decades of low skill immigration. After the boom years in the aftermath of WWII, immigration was initially facilitated yet global quotas put in place in the 1970s proofed to be largely ineffective as major channels of immigration were de-facto exempted (Sheldon, 2007). In the early 1990s policy makers decided to discriminate between immigrants from EU/EFTA countries and third party countries. The goal of this distinction was to facilitate immigration from EU/EFTA countries while immigration from other countries was subject to a stronger focus on highly educated workers with larger obstacles for the low skilled (see Bundesrat, 1991 and Bundesrat, 2002). De-facto, however, global quotas for immigrants from all origins were maintained. With the enactment of the Agreement of Free Movement of Persons with the EU in 2002, the distinction between immigrants from EU and Non-EU countries became even more pronounced. While quotas for Non-EU citizens were kept in place, the integration of the Swiss and European labour market followed a specific schedule. From June 1 2002 to May 31 2004, labour market restrictions and quotas remained in place for workers from all origin countries. Between June 1 2004 and May 31 2007, the restriction to hire natives with priority and controls of wage and working conditions for immigrant workers from EU17 member states and EFTA countries was abolished.[40] After June 1 2007, workers from EU17/EFTA countries had in principle unrestricted access to the Swiss labour market while quotas and labour market restrictions

[40] EU17 includes Belgium, Germany, France, Italy, Luxembourg, the Netherlands, Denmark, Ireland, United Kingdom, Greece, Portugal, Spain, Finland, Austria, Sweden, Cyprus and Malta. EFTA include Iceland, Norway and Liechtenstein.

were kept in place for the Eastern European countries (EU8) until April 30 2011 (SECO, 2014).[41]

In the public policy debate in Switzerland, it is often stipulated that the integration into the European labour market caused a major upgrading in the skill composition of immigrants (Economiesuisse, 2011). Yet, the causal link between the change in policy and the change in the skill composition has not been analysed rigorously so far. Interestingly, as Panel A of figure 3.5 shows, the share of highly educated workers increased sharply both for EU and Non-EU immigrants in the 1990s but levelled off for immigrants from the EU in the last decade. On the other hand, the share of low educated workers decreased throughout for both groups while, again, this fall levelled off in case of EU immigrants during the last decade. An inspection of group specific growth rates presented in figure A.2 in the appendix reveals that the increase in the share of highly educated workers in the 1990s is driven by the fact that this was the only education group experiencing non-negative growth for both EU and Non-EU countries whereas the other two education groups experienced a reduction in their number of workers. Between 2000 and 2010, however, only the number of highly and middle educated workers from Non-EU countries increased while the number of low educated workers decreased. For EU countries on the other hand, the number of workers increased in all education groups between 2000 and 2010, most interestingly also for low educated workers.

Figure 3.5: Education Group Share for Recent Immigrants from EU and Non-EU Countries, 1980 - 2010



Notes: High educated workers have a tertiary degree, middle educated workers a secondary degree and low educated workers compulsory schooling or less. Share of tertiary educated workers among each nationality group. Swiss Census 1980 - 2010.

Measuring the Effect of Changes to Immigration Policy

The existing evidence on the response of the skill composition of immigrants to changes in immigrants restrictions is rather scarce. With respect to the magnitude of immigration

[41] EU8 includes Estonia, Latvia, Lithuania, Poland, Slovakia, Slovenia, Hungary and the Czech Republic.

flows more generally, there is some agreement that changes in immigration restrictions affect immigration flows rather immediately and strongly (Mayda, 2010; Ortega and Peri, 2013) and may also influence the region immigrants originate from if restrictions are discriminatory (Clark et al., 2007). Among the only two studies investigating the effects of the policy on the skill compositions directly, Kato and Sparber (2013) find that the general reduction in the number of available H-1B visas in 2003 in the U.S. disproportionally discouraged high-ability students from pursuing an education at U.S. universities.[42] On the other hand, Huber and Bock-Schappelwein (2014) find that Austria's accession to the European Economic Area (EEA) in 1994 and the related full liberalisation of immigration from European countries reduced the share of low educated permanent immigrants from the EEA compared to other countries.

To analyse the effect of new immigration laws empirically, we exploit the fact that the policy distinguished between immigrants from EU and immigrant from other origin countries and that the policy changed over time. As the liberalisation of the Swiss labour market for EU citizens after 2002 is the most far-reaching change in immigration policy, we start investigating whether the skill composition of immigrants from European origin countries changed differentially after 2002 compared to Non-European immigrants controlling for economic drivers of immigrant sorting. Specifically, we augment regression specification (3.7) in the following way:

$$\begin{aligned} \Delta EDUSH^E_{j,o,\tau} \quad = \quad & \beta^E_1 RSH_{j,t} + \beta^E_2 \Delta X^E_{o,\tau} + \beta^E_3 \Delta EDUSH^E_{o,\tau} \\ & + \beta^E_4 \mathrm{EU}^{2000}_{o,t} + \alpha_\tau + \alpha_o + \alpha_c + \epsilon_{j,o,\tau} \end{aligned} \tag{3.11}$$

where $\mathrm{EU}^{2000}_{o,t}$ is one for all EU countries affected by the AFMP in the decade between 2000 and 2010 and zero otherwise.[43] β^E_4 then measures the degree to which education shares of immigrants from EU countries changed differentially between 2000 and 2010 compared to the change of EU and Non-EU immigrants prior to the AFMP conditional on covariates. Hence, the policy effect, as we measure it here, is the deviation of the change in the education shares of the affected group (the EU countries) from a common trend which immigrants from all countries share due to the differential policy treatment. The differential policy treatment is the combination of abolishing the quotas for EU citizens while sustaining quotas together with requirements to the skill for non-EU citizens. Crucially, the identification of β^E_4 as the causal effect of the policy hinges on the assumption

[42] Kato and Sparber (2013) exploit the fact that workers from five countries were de facto exempted from the reduction in the H-1B visa quota in a difference-in-difference analysis of student SAT scores.

[43] More formally, $\mathrm{EU}^{2000}_{o,t}$ is the product of two indicators, one for EU origin countries and one for the last decade, i.e. $\mathrm{EU}^{2000}_{o,t} = [1(o \in EU) \times 1(\tau = 2000s)]_{o,t}$.

that there are no factors omitted from the regression which could have lead to differential trends in the change of the skill composition of immigrants from EU vs Non-EU countries after 2002. As we control for a large range of time-varying labour market characteristics in origin countries and fixed origin country characteristics we are confident to address these concerns already to a large extend.[44] Yet, as the discussion of the change in immigration policy in Switzerland since the 1980s suggests, it is likely that changes to the skill composition of immigrants from the EU and other countries started to follow different trends already after 1990. To account for this possibility, we check the robustness of β_4^E by controlling for separate trends in a second step.[45]

In the framework of Grogger and Hanson (2011), changes to the immigration policy alter, ceteris paribus, the relative costs of immigration in the sorting Equation (3.4), i.e. $\left(g^H - g^M\right)_{j,o,t}$ and $\left(g^M - g^L\right)_{j,o,t}$. Immigrant sorting is affected, if costs change differentially for education groups. For instance, if migration costs fall more for middle educated than for highly educated workers, i.e., $\Delta\left(g^H - g^M\right)_{j,o,t} > 0$, the inflow of highly educated workers relative to middle educated workers will fall. It is natural to assume that the integration into the European labour market reduced migration costs for all education groups. Yet, the effect of the abolishing immigration quotas has most likely affected the net benefits of education groups differentially. As we lack direct information on immigration costs which vary across origin countries, education groups and over time, we can only approximate the effect of the changes in immigration policy *indirectly* by analysing the differential response of immigrants from affected and not affected countries conditional on a large set of covariates. Thus, what we capture with β_4^E is the differential change in net benefits of migration of education groups.

Discussion of Main Results

Table 3.4 shows the results of estimating versions of specification (3.11) for each education group. For comparison, column 1 repeats the baseline specification without origin country labour market controls. Column 2 reports the effect of introducing the policy dummy, $\text{EU}_{o,t}^{2000}$. As can be seen, in case of EU countries between 2000 and 2010, the increase in the share of highly educated immigrants was about 12 percentage points lower compared to the

[44]Using region specific education group shares for each origin country in 1980 to control for mean reversion delivers similar results. Results available upon request.

[45]Another important assumption for the interpretation of β_4^E as a causal effect is the exogeneity of $\text{EU}_{o,t}^{2000}$. This essentially means that liberalisation measures were not introduced for immigrants of those countries whose skill composition showed a favourable trend from the perspective of the policy maker. We think that this assumption can be justified on the grounds that free movement of persons with the EU was not a sought after goal of Swiss policy makers. To the contrary, the AFMP was a request of the European Union for a larger deal of bilateral packages (involving mostly trade agreements) between the EU and Switzerland.

control group. The effect on middle educated immigrants is estimated around zero whereas the effect is positive and significant for low educated immigrant workers (15 percentage points higher). Next, we analyse whether this effect is sensitive to controlling for labour market characteristics in origin countries by switching in the change in educational wage differences (column 3) or the growth rate of real GDP per capita and the change in the Gini (column 4). Reassuringly, point estimates remain within the 95%-confidence bands of the effect estimated in column 2. When we including all origin country controls in column 5, the estimated effect of the policy is still significant and negative in the case of highly educated workers and strongly significant and positive in the case of low educated workers. Although the AFMP eventually liberalised Swiss labour market access for all European countries, it is likely that the differential abolition of quotas for immigrants from EU17 and EU10 countries led to a heterogenous response in these two cases. We account for this possibility by allowing for separate effects of the AFMP policy on the skill composition of immigrants from both groups, $\mathrm{EU17}_{o,t}^{2000}$ and $\mathrm{EU10}_{o,t}^{2000}$ respectively. Column 6 shows that the estimated effect for all European countries is actually a weighted average of a slightly larger and significant effect for old European member states and an effect which is estimated around zero for new member states of the EU. This makes sense since old member states (EU17) have been "treated" with completely unrestricted access already since 2007 whereas access for immigrants from new member states (EU10) was still subject to quotas until 2011. These findings suggest that the opening of the Swiss labour market had, if anything, an adverse effect on the skill composition of immigrants.

Table 3.4: The Effect of Immigration Policy on the Change in Education Group Shares of Recent Immigrants, 1980 - 2010, 2SLS Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
			A. Dependent Variable: Change of Highly Skill Labour Share			
$RSH_{j,t}$	0.337	0.323	0.369	0.366	0.365	0.363
	[0.106]***	[0.100]***	[0.0955]***	[0.0971]***	[0.0971]***	[0.0955]***
$\Delta EDUSH^{H}_{o,\tau}$	1.008	0.892	0.876	0.871	0.840	0.809
	[0.303]***	[0.236]***	[0.179]***	[0.190]***	[0.210]***	[0.223]***
$\mathrm{EU}^{2000}_{o,\tau}$		-0.117	-0.175	-0.0874	-0.0898	
		[0.0650]*	[0.0639]***	[0.0481]*	[0.0478]*	
$\mathrm{EU17}^{2000}_{o,\tau}$						-0.101
						[0.0534]*
$\mathrm{EU10}^{2000}_{o,\tau}$						-0.0124
						[0.0506]
R-squared	0.040	0.063	0.095	0.106	0.109	0.110
F-Stats	49.70	49.70	48.22	47.95	48.01	47.93
			B. Dependent Variable: Change of Middle Skill Labour Share			
$RSH_{j,t}$	-0.285	-0.289	-0.291	-0.295	-0.290	-0.289
	[0.112]**	[0.109]***	[0.109]***	[0.109]***	[0.110]***	[0.110]***
$\Delta EDUSH^{M}_{o,\tau}$	0.833	0.838	1.001	0.922	1.006	0.962
	[0.226]***	[0.235]***	[0.263]***	[0.228]***	[0.233]***	[0.242]***
$\mathrm{EU}^{2000}_{o,\tau}$		-0.0265	-0.00199	0.0220	0.00117	
		[0.0382]	[0.0244]	[0.0436]	[0.0430]	
$\mathrm{EU17}^{2000}_{o,\tau}$						0.0103
						[0.0421]
$\mathrm{EU10}^{2000}_{o,\tau}$						-0.0760
						[0.0922]
R-squared	0.050	0.051	0.081	0.071	0.083	0.084
F-Stats	49.75	49.77	48.04	47.79	47.77	47.72
			C. Dependent Variable: Change of Low Skill Labour Share			
$RSH_{j,t}$	-0.0524	-0.0331	-0.0796	-0.0711	-0.0715	-0.0720
	[0.0980]	[0.0900]	[0.0944]	[0.0942]	[0.0956]	[0.0952]
$\Delta EDUSH^{L}_{o,\tau}$	0.786	0.718	0.611	0.702	0.703	0.697
	[0.232]***	[0.224]***	[0.143]***	[0.155]***	[0.151]***	[0.154]***
$\mathrm{EU}^{2000}_{o,\tau}$		0.146	0.177	0.0700	0.0722	
		[0.0679]**	[0.0595]***	[0.0283]**	[0.0299]**	
$\mathrm{EU17}^{2000}_{o,\tau}$						0.0699
						[0.0310]**
$\mathrm{EU10}^{2000}_{o,\tau}$						0.0926
						[0.0630]
R-squared	0.036	0.076	0.132	0.155	0.155	0.155
F-Stats	49.67	49.68	48.01	47.77	47.66	47.60
Change in educ. wage differences	No	No	Yes	No	Yes	Yes
Change in GDP pc and Gini	No	No	No	Yes	Yes	Yes
Observations	4,144	4,144	2,987	2,987	2,987	2,987

Notes: ***, **, *, denote statistical significance at the 1%, 5% and 10% level, respectively. Robust standard errors (clustered by Canton and origin country) are given in parentheses. All models include fixed effects for Cantons, origin countries and decades. Regressions are weighted using the total number of recent immigrants from origin country o in destination j at the beginning of the decade as weight. $RSH_{j,t}$ is instrumented with $\widetilde{RSH}_{j,1970}$. $\Delta EDUSH^{E}_{o,\tau}$ is the decennial change in the share of education group $E \in \{H, M, L\}$ in origin country o and decade τ. $\mathrm{EU}^{2000}_{o,\tau}$ is one for EU countries between 2000 and 2010. $\mathrm{EU17}^{2000}_{o,\tau}$ and $\mathrm{EU10}^{2000}_{o,\tau}$ are one for EU17 and EU10 countries, respectively, between 2000 and 2010.

In contrast, Huber and Bock-Schappelwein (2014) find that the liberalisation of immigration from European countries into Austria has led to a fall of low-skill immigration compared to other countries. How can their findings be reconciled with ours? From a theoretical point of view, the answer is that the effect of changes in immigration restrictions on the skill composition of immigrants depends on the education-type of the so-called '*marginal immigrant*', i.e. the skill group for which immigration costs and benefits roughly equalise prior to the policy change.[46] Huber and Bock-Schappelwein (2014) point out that Austria *"had the third lowest return to education for men and the 13th lowest for women among 26 developed countries."* Consequently, immigration to Austria was selected from the lower tail of the skill distribution in the pre-liberalisation period (i.e., the relative benefits from migration was higher for low-skill than for high-skill migrants). The subsequent reduction of immigration costs increased the net-benefits of immigration for all education groups but changed them from negative to positive for more skilled workers in the middle of the ability distribution whose net-benefits were close to zero before. In the Swiss case, immigrants were already positively selected prior to the liberalisation. In addition, the immigration policy of the early 1990s had a general focus on restricting immigration for low skilled immigrants from Non-EU countries. Thus, most likely the marginal immigrant for whom net-benefits of migration to Switzerland was zero prior to the AFMP would have been located towards the lower end of the skill distribution whereas net benefits for highly educated foreign workers were clearly positive. Consequently, the fall of migration costs across the board for EU-origin countries had a larger effect on the sign of net-benefits of migration for low educated workers.

Robustness of Policy Effect

As already mentioned, interpreting the estimations above as a causal effect of the AFMP hinges on the assumption that the evolution of the immigrants' skill composition from EU and Non-EU countries was subject to similar trends in trends prior to the AFMP. The validity of this assumption may be questionable, especially since policy makers already started to discriminate between the two country groups in the 1990s. Therefore, in table 3.5 we control for pre-trends in our difference-in-difference analysis in various ways. Again for comparison, column 1 repeats the specification in column 5 of table 3.4. Column 2 allows for differential linear time trends of EU and Non-EU countries which decreases (increases) the point estimate of the effect for highly (low) educated immigrants slightly while the point estimate for middle educated workers is still zero. In column 3, we allow for an additional differential change in the skill composition of EU immigrants in the 1990s ($\mathrm{EU}^{1990}_{o,t}$), when policy makers introduced the discrimination regime between EU

[46]The assumption here is that net-benefits are monotone in skills like in Borjas (1987).

and Non-EU countries for the first time. Interestingly, the effect becomes only slightly smaller in absolute value for highly educated workers whereas the effect for low educated workers drops almost by half. Although both effects are not significant for each education groups individually, the hypothesis that both effects are jointly zero can be rejected on the 10% level for highly and on the 5% level for low educated immigrants. In addition, we can reject the hypothesis that the differential change in the skill composition of EU immigrants was similar in both decades on the 5% level and at the 1% level, respectively. Unsurprisingly, analysing this pre-trends separately for EU17 and EU10 origin countries paints a similar picture with effects for EU17 countries generally being larger in absolute magnitude whereas the effect for EU10 countries are clustered around zero. From this analysis, we cannot completely reject that changes to immigration policy had no effect on the skill composition of immigrants. However, immigration policy was clearly of secondary importance compared to economic drivers like the demand in destinations and education supply in origin countries.

Table 3.5: The Effect of Immigration Policy on the Change in Education Group Shares of Recent Immigrants, 1980 - 2010, Controlling for Pre-Trends, 2SLS Estimates

	(1)	(2)	(3)
A. Dependent Variable: Change of Highly Skill Labour Share			
$RSH_{j,t}$	0.365	0.365	0.365
	[0.0971]***	[0.0972]***	[0.0972]***
$\Delta EDUSH^{H}_{o,t}$	0.840	0.834	0.834
	[0.210]***	[0.252]***	[0.252]***
$\mathrm{EU}^{2000}_{o,t}$	-0.0898	-0.0965	-0.0864
	[0.0478]*	[0.0525]*	[0.0642]
$\mathrm{EU}^{1990}_{o,t}$			0.00502
			[0.0393]
R-squared	0.109	0.109	0.109
F-Stats	48.01	47.95	47.95
H0: $\mathrm{EU}^{1990}_{o,t} = \mathrm{EU}^{2000}_{o,t} = 0$			0.0946
H0: $\mathrm{EU}^{1990}_{o,t} = \mathrm{EU}^{2000}_{o,t}$			0.0358
B. Dependent Variable: Change of Middle Skill Labour Share			
$RSH_{j,t}$	-0.290	-0.290	-0.290
	[0.110]***	[0.110]***	[0.110]***
$\Delta EDUSH^{M}_{o,t}$	1.006	1.035	1.035
	[0.233]***	[0.251]***	[0.251]***
$\mathrm{EU}^{2000}_{o,t}$	0.00117	-0.0327	0.0196
	[0.0430]	[0.0377]	[0.0696]
$\mathrm{EU}^{1990}_{o,t}$			0.0261
			[0.0436]
R-squared	0.083	0.084	0.084
F-Stats	47.77	47.73	47.73
H0: $\mathrm{EU}^{1990}_{o,t} = \mathrm{EU}^{2000}_{o,t} = 0$			0.685
H0: $\mathrm{EU}^{1990}_{o,t} = \mathrm{EU}^{2000}_{o,t}$			0.852
C. Dependent Variable: Change of Low Skill Labour Share			
$RSH_{j,t}$	-0.0715	-0.0710	-0.0710
	[0.0956]	[0.0951]	[0.0951]
$\Delta EDUSH^{L}_{o,t}$	0.703	0.714	0.714
	[0.151]***	[0.157]***	[0.157]***
$\mathrm{EU}^{2000}_{o,t}$	0.0722	0.101	0.0560
	[0.0299]**	[0.0404]**	[0.0351]
$\mathrm{EU}^{1990}_{o,t}$			-0.0227
			[0.0233]
R-squared	0.155	0.155	0.155
F-Stats	47.66	47.64	47.64
H0: $\mathrm{EU}^{1990}_{o,t} = \mathrm{EU}^{2000}_{o,t} = 0$			0.0254
H0: $\mathrm{EU}^{1990}_{o,t} = \mathrm{EU}^{2000}_{o,t}$			0.00823
Trend*EU	No	Yes	No
Observations	2,987	2,987	2,987

Notes: ***, **, *, denote statistical significance at the 1%, 5% and 10% level, respectively. Robust standard errors (clustered by Canton and origin country) are given in parentheses. All models include fixed effects for Cantons, origin countries and decades. Regressions are weighted using the total number of recent immigrants from origin country o in destination j at the beginning of the decade as weight. $RSH_{j,t}$ is instrumented with $\widetilde{RSH}_{j,1970}$. $\Delta EDUSH^{E}_{o,\tau}$ is the decennial change in the share of education group $E \in \{H, M, L\}$ in origin country o and decade τ. $\mathrm{EU}^{2000}_{o,\tau}$ and $\mathrm{EU}^{1990}_{o,\tau}$ are one for EU countries between 2000 and 2010 and 1990 and 2000, respectively.

3.4.4 Extensions

A. Benchmarking Factors That Drive the Skill Composition

Average Changes in the Skill Composition To gauge the economic magnitude of our estimates, we compare the observed change in the skill composition of immigrants with its change predicted by relative labour demand in destinations, the skill supply in origin countries and the potential effects of immigration policy. We illustrate these effects for an average commuting zone using our estimates from table 3.4 (column 5).

Between 1980 and 2010, commuting zones in Switzerland experienced an average increase in the share of highly educated immigrants of 7.7 percentage points per decade (pp/d), and a decrease of 0.6 pp/d and 7.2 pp/d of middle and low educed recent immigrants, respectively.[47] Clearly, part of these changes are just driven by the fact that the education supply changed in the countries where these newly arriving immigrants originate from. On average, the share of highly and middle educated workers in the origin countries increased by 3.1 and 8.9 pp/d, respectively, whereas the share of low skill workers decreased by 12 pp/d. Our coefficients of the supply measure imply that these changes would have translated almost 1:1 into the changes in the skill composition of newly arriving immigrants in Switzerland: The share of highly and middle educated would increase by 2.57 pp/d (0.83×0.031) and 9 pp/d (1×0.089), respectively, and the share of low educated would decrease by 8.86 pp/d (0.73×-0.12). Thus, the changes in supply clearly underestimate the observed change of highly educated workers, massively overestimate the change in the share of middle educated (with the wrong sign) and are about right concerning the share of low educated immigrants.

This highlights the importance of accounting for changes to the relative demand for workers with different educational backgrounds. The coefficients of $RSH_{j,t}$ imply that an average commuting zone with a share of 0.33 in routine employment in 1980 would have experienced an increase in the share of highly educated recent immigrants of 12 pp/d (0.36×0.33) and a decrease in the share of middle educated immigrants of -10 pp/d (-0.29×0.33) whereas the impact on low educated workers cannot be distinguished from zero. Adding both the effects of supply and demand in destinations together, our estimations imply that the share of highly educated among recent immigrants increased by roughly 14.7 pp/d whereas the share of middle and low educated decreased by 0.7 and 8.8 pp/d.

Accounting for the effect of the policy, the increase in the share of highly educated workers was substantially lower for EU immigrants between 2000 and 2010 and amounted

[47] These averages are calculated using the population weight of country groups in destinations at the beginning of the decade.

to only 5.7 pp ($14.7 - 8.98$). On the other hand, the share of low educated workers from the EU decreased at a slower rate of 1.7 pp ($-8.8 + 7.16$).

Regional Heterogeneity The importance of relative labour demand as driver of immigrant skills can be illustrated nicely by contrasting regions which were exposed to very different demand shifts. With a share of 40% and 26% of employment in routine intensive occupations in 1980, Basel and Zurich Oberland, the rural area outside of the city of Zurich, were at the 75th and 25th percentile rank of the routine employment distribution. Over the next three decades, the share of highly educated increased from 27% to 71% (14 pp/d) in Basel, while the share of middle and low educated decreased from 25% to 20% (-1.6 pp/d) and 48% to 8% (-13.3 pp/d), respectively. In Zurich Oberland, in the meantime, the shares highly and middle immigrants increased from 8% to 34% (8 pp/d) and from 17% to 39% (7 pp/d), respectively, whereas the share of low educated fell from 74% to 26% (-15 pp/d). Although both regions faced very similar changes in the educational supply of immigrants, their skill composition changed very differently.[48] The difference in the routine intensity, however, explains to some degree the differential changes. The 13 pp difference in routine intensity translates into a 5 pp/d higher increase in the share of highly educated workers (of the 6 pp/d difference observed) and a 4 pp/d lower increase in the share of middle educated (8 pp/d difference observed).

C. Zero or Missing Bilateral Immigration Stocks

As pointed out in Section 3.3.1, we set cells with missing information of recent immigrants to zero for the Censuses 1980 to 2000. In so doing, we include many cells which would have otherwise dropped out of the sample. To demonstrate that our results are not sensitive to this treatment, table A.8 shows our baseline specification (cf. table 3.2) excluding these cells. Our results again prove to be remarkably stable in light of the much smaller number of observations we have with this sample.

C. Weighting of Cells

Next, we explore the robustness of the regressions to different weighting schemes. In our baseline regressions, we weighted cells using the total number of immigrants at the beginning of the decade as weights. Regression coefficients then, should reflect average changes in the immigrant population, yet the picture for average changes on the local level could be slightly different as these weights not necessarily reflect the different sizes

[48] As both regions are German speaking, we abstract from the fact here, that both regions might attract immigrants from different origin countries and that the distribution of origin countries across regions might have some power of explaining observed changes in the skill composition.

of local labour markets. To check the influence of weighting, we weight instead using the total number of workers in table A.7 in the appendix. While the OLS coefficients are estimated less precise, coefficients for our 2SLS results remain remarkably stable.

3.5 Conclusion

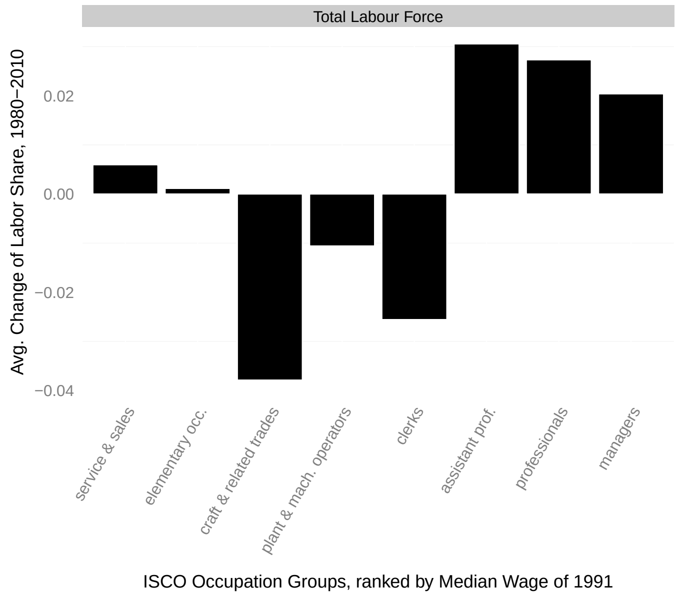
A little acknowledged feature of international migration to rich countries is that newly arriving immigrants are increasingly highly educated. Since 1980, the share of immigrants workers with tertiary education rose on average 15 percentage points in OECD countries whereas educational upgrading soared especially in some countries, such as Canada, Australia, the United Kingdom or Switzerland. In this paper, we analyse the determinants of the skill composition of newly arriving immigrants from a long-run perspective using a framework of immigrant selection and sorting suggested by Grogger and Hanson (2011). Applying this framework to one particular destination country, Switzerland between 1980 and 2010, we can analyse the importance of origin country push drivers, such as changes in the education supply and the relative demand for workers with different educational background in origin countries, as well as economic pull drivers, such as changing relative demand for education groups in destinations, and changes to immigration policy or other migration costs. We focus on Switzerland, which continuously showed very high immigration rates and exhibited dramatic changes in the skill composition of immigrants. Unlike other 'traditional' immigration countries, however, the recent integration of Switzerland into the European labour market in 2002 constitutes an interesting policy experiment in which immigration restrictions were abolished for immigrants from the EU but not for immigrants from other countries. This allows studying the effect of changing immigration restrictions on the selection of immigrants with different educational backgrounds using a difference-in-difference design.

Our findings suggest that changes of education supply in origin countries and shifts to the relative demand for education groups stand out as the two most important drivers. Yet, while supply alone predicts only a modest increase in the case of highly educated workers and a large increase of middle educated workers, one particular demand channel, the polarisation of labour demand induced by the adoption of computer capital, is crucial to explain the sharp increase in highly educated workers and the mere stabilisation of the share of middle educated immigrant workers. Furthermore, our analysis reveals that the abolishment of quotas for immigrants from European origin countries had a small effect but slightly reversed the trends in the change of the skill composition. Between 2000 and 2010, the share of highly educated workers increased at a significantly lower rate among recent immigrants from EU countries compared to other countries and the share of low educated workers decreased at a significantly lower rate. In the discussion of our results we argue that this finding can be reconciled with a situation in which immigrants were already very positively selected prior to the change in immigration policy in 2002. Thus, the reduction of immigration restriction for all immigrants from European countries increased the propensity to immigrate more for education groups at the lower end of the skill distribution compared to highly educated immigrants for whom the immigration was already beneficial prior to the policy change.

3.A Appendix

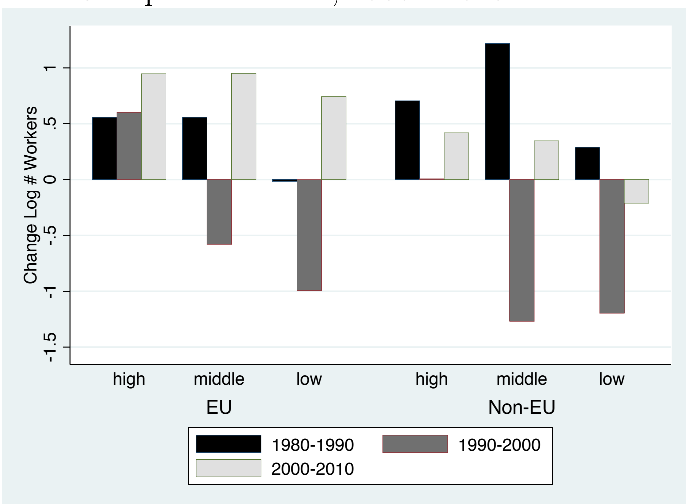
3.A.1 Figures

Figure A.1: Average Decennial Change in Employment Shares of Occupation Groups of Total Labour Force, 1980 - 2010



Notes: The graph shows for each ISCO main occupation group (omitting agriculture) the average decennial growth of its employment share (in full time equivalents) on the total labour force between 1980 and 2010. Occupation groups are ranked by their median wage taken from the Swiss Labor Force Survey (1991 to 1993 pooled). Employment data from Swiss Census 1980 to 2010.

Figure A.2: Change in the Log Number of Immigrant Workers from EU and Non-EU Countries by Education Group and Decade, 1980 - 2010



Notes: High educated workers have a tertiary degree, middle educated workers a secondary degree and low educated workers compulsory schooling or less. Share of tertiary educated workers among each nationality group. Swiss Census 1980 - 2010.

3.A.2 Tables

Table A.1: Summary Statistics

Variable	Mean	Std. dev.	Min.	Max.	# Obs.
$\Delta EDUSH^{H}_{j,o,\tau}$	0.077	0.146	-1	1	4304
$\Delta EDUSH^{M}_{j,o,\tau}$	-0.006	0.161	-1	1	4304
$\Delta EDUSH^{L}_{j,o,\tau}$	-0.071	0.147	-1	1	4304
$RSH_{j,t}$	0.295	0.060	0.136	0.434	6855
$\widetilde{RSH}_{j,1970}$ (all)	0.330	0.052	0.159	0.584	6855
$\Delta EDUSH^{H}_{o,\tau}$	0.031	0.028	-0.049	0.132	6855
$\Delta EDUSH^{M}_{o,\tau}$	0.089	0.062	-0.297	0.441	6855
$\Delta EDUSH^{L}_{o,\tau}$	-0.120	0.060	-0.464	0.287	6855
$IMSH_{j,o,1970}$	0.019	0.031	0.000	0.179	6855
$OFFSH^{GMS}_{j,\tau}$	-0.632	0.596	-2.167	2.140	6855
$OFFSH^{BK}_{j,\tau}$	2.831	2.503	-3.312	6.934	6855
$OFFSH^{AD}_{j,\tau}$	1.218	1.300	-3.004	3.833	6855
$\Delta\left(w^{H}-w^{M}\right)_{o,\tau}$	5569.208	6579.263	-1143.361	23269.789	4661
$\Delta\left(w^{M}-w^{L}\right)_{o,\tau}$	2521.276	2053.341	-1339.523	7029.826	4661
$\Delta GDPPC_{o,\tau}$	0.015	0.018	-0.028	0.097	6685
$\Delta GINI_{o,\tau}$	0.025	0.045	-0.034	0.147	4661

Notes: $\Delta EDUSH^{E}_{j,o,\tau}$ is the change in the share of education group $E \in \{H, M, L\}$ of immigrants from origin country o in destination j in decade τ. $RSH_{j,t}$ is share of employment of commuting zone j working in routine occupations as defined in Equation (3.9) at the beginning of the decade. $\widetilde{RSH}_{j,1970}$ is the routine share in 1970 defined by Equation (3.10). $\Delta EDUSH^{E}_{o,\tau}$ is the decennial change in the share of education group $E \in \{H, M, L\}$ in origin country o and decade τ. $\Delta\left(w^{M}-w^{L}\right)_{o,\tau}$ and $\Delta\left(w^{M}-w^{L}\right)_{o,\tau}$ are the decennial change in the wage differential between highly and middle and middle and low educated workers in origin country o and decade τ, respectively. $\Delta GDPPC_{o,\tau}$ and $\Delta GINI_{o,\tau}$ represent the decennial change in GDP per capita and the Gini index in origin country o and decade τ. $IMSH_{j,o,1970}$ is the population share of immigrants from origin country o in destination j in 1970. $OFFSH^{GMS}_{j,\tau}$, $OFFSH^{BK}_{j,\tau}$ and $OFFSH^{AD}_{j,\tau}$ represent measures of offshoreability using the definitions of Goos et al. (2011), Blinder and Krueger (2013), Autor and Dorn (2013), respectively. See section 3.3.1 and the online data appendix for a more detailed description of variables. Swiss Census 1980 to 2010.

Table A.2: List of Origin Countries

Country	# Immigrants	Group	Country	# Immigrants	Group
Germany	120040	EU17	Balkan Countries	72996	Non-EU
Italy	119868	EU17	Turkey	18763	Non-EU
Portugal	60956	EU17	United States	15774	Non-EU
Spain	57529	EU17	Canada	5101	Non-EU
France	53866	EU17	India	3927	Non-EU
United Kingdom	20912	EU17	China	2248	Non-EU
Austria	19210	EU17	Japan	2174	Non-EU
Czech Rep. & Slovakia	11209	EU10	Tunisia	1932	Non-EU
Netherlands	8792	EU17	Algeria	1226	Non-EU
Belgium	5339	EU17	Israel	1177	Non-EU
Poland	4280	EU10	Vietnam	1089	Non-EU
Sweden	4028	EU17	Chile	1011	Non-EU
Hungary	3759	EU10	Iran	936	Non-EU
Greece	3316	EU17			
Denmark	2708	EU17			
Romania	2569	EU10			
Finland	2237	EU17			

Notes: # Immigrants represents the cumulative number of recent immigrants in all destinations j between 1980 and 2010. Balkan countries and the Czech Republic and Slovakia were not distinguished in the Census prior to 2010. Swiss Census 1970 - 2010.

Table A.3: Task Content of Education Groups

	Task Content			
Education Group	abstract	routine	manual	RTI
High	1.12	-0.30	-0.19	-0.37
Middle	-0.06	0.12	-0.09	0.11
Low	-0.31	-0.05	0.19	-0.02

Notes: Task measures taken from DOT as described in section 3.3. Routine intensity (RTI) calculated as in equation (3.8). Task measures and RTI scores are first standardised then and averaged over all workers in an education group using employment weights. Agricultural workers have been omitted from this table. Swiss Census 1980.

Table A.4: Employment Shares of Occupation Groups, in Percent by Nationality, 1970 - 2010

		Occupation Group Shares (in %)				Change (in %-points)
ISCO88 Code	Occupation	1980	1990	2000	2010	1980-2010
		A. Natives				
1	Managers	6.72	11.21	11.13	11.36	4.64
2	Professionals	9.68	11.95	15.22	17.43	7.75
3	Technicians and Associate Prof.	13.98	20.99	22.03	23.97	9.99
4	Clerks	21	16.32	14.67	11.35	-9.65
7	Craft and Related Trades	23.31	18.35	16.02	14.16	-9.15
8	Plant & Machine Operators	8.05	5.79	4.6	3.8	-4.25
9	Elementary Occupations	4.51	3.48	3.23	3.81	-0.70
5	Service and Sales	12.75	11.9	13.11	14.12	1.37
		B. Recent Immigrants				
1	Managers	2.74	4.68	13.2	14.61	11.87
2	Professionals	9.01	8.79	23.38	20.43	11.42
3	Technicians and Associate Prof.	7.52	12.92	17.7	16.63	9.11
4	Clerks	7.21	5.62	6.97	6.39	-0.82
7	Craft and Related Trades	42.3	29.09	10.67	14.69	-27.61
8	Plant & Machine Operators	7.63	6.14	3.14	3.9	-3.73
9	Elementary Occupations	5.09	7.87	5.78	8.72	3.63
5	Service and Sales	18.52	24.9	19.16	14.63	-3.89
		C. Total Workforce				
1	Managers	6.04	10.29	10.79	11.63	5.59
2	Professionals	9.49	11.27	14.91	17.13	7.64
3	Technicians and Associate Prof.	12.74	19.2	20.73	21.96	9.22
4	Clerks	18.89	14.64	13.78	10.42	-8.47
7	Craft and Related Trades	26.5	20.67	16.68	14.81	-11.69
8	Plant & Machine Operators	8.72	6.5	5.14	4.33	-4.39
9	Elementary Occupations	4.79	4.39	3.93	5.17	0.38
5	Service and Sales	12.83	13.05	14.04	14.55	1.72

Notes: Employment shares (in full time equivalents) of ISCO main occupation groups (omitting agriculture). Occupation groups are ranked in a descending order by their median wage taken from the SLFS 1991 to 1993. Employment data from Swiss Census 1980 to 2010

Table A.5: First Stage Estimates for Decennial Routine Intensity used in Baseline Estimates for the Change in the Employment Share of Highly Educated Immigrants (Table 3.2: Panel A, Column 4)

Dep. var.: Decennial Routine Intensity of a Comm. Zone, $RSH_{j,t}$

Sample	Pooled	1980	1990	2000
	(1)	(2)	(3)	(4)
$\widetilde{RSH}_{j,1970}$	0.789	1.188	0.647	0.558
	[0.112]***	[0.160]***	[0.098]***	[0.058]***
Observations	4,144	1,744	2,021	379
R-squared	0.522	0.715	0.624	0.631
F-Stats	49.69	54.76	43.36	91.37

Notes: ***, **, *, denote statistical significance at the 1%, 5% and 10% level, respectively. Robust standard errors (clustered by Canton and origin country) are given in parentheses. All models include fixed effects for Cantons, origin countries. Column 1 pools data from three decades, 1980 to 2010, and uses fixed effects for decades too. Column 2 to 4 show separate estimates for a single decade. Regressions are weighted using the total number of recent immigrants from origin country o in destination j at the beginning of the decade as weight. $RSH_{j,t}$ is instrumented with $\widetilde{RSH}_{j,1970}$.

Table A.6: Estimation of Equation (3.5) and Equation (3.6): Determinants of the Change in Log Employment Ratios of Education Groups of Recent Immigrants, 1980 - 2010, OLS and 2SLS Estimates

	OLS			2SLS				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Dependent Variable: Change of High Skill relative to Middle Skill Migration								
$RSH_{j,t}$	0.364	0.247	0.160	1.054	1.202	1.127	1.153	0.926
	[0.712]	[0.743]	[0.700]	[0.679]	[0.671]*	[0.639]*	[0.648]*	[0.550]*
$\Delta\left(\ln \frac{L^H}{L^M}\right)_{o,\tau}$		0.872	0.776		0.867	0.772	0.780	
		[0.137]***	[0.055]***		[0.134]***	[0.049]***	[0.094]***	
$\Delta\left(w^H - w^M\right)_{o,\tau}$		-1.01e-05	-2.00e-05		-9.24e-06	-1.91e-05		
		[0.000]	[0.000]***		[0.000]	[0.000]***		
$\Delta GDPPC_{o,\tau}$			0.0553			0.0548	0.0456	
			[0.010]***			[0.010]***	[0.009]***	
$\Delta GINI_{o,\tau}$							-0.612	
							[0.289]**	
R-squared	0.000	0.059	0.088	-0.001	0.056	0.085	0.080	0.167
F-Stats				41.90	41.23	41.04	40.97	40.42
B. Dependent Variable: Change of Middle Skill relative to High Skill Migration								
$RSH_{j,t}$	-1.610	-1.581	-1.703	-0.685	-0.580	-0.689	-0.680	-0.711
	[0.566]***	[0.581]***	[0.592]***	[0.674]	[0.775]	[0.769]	[0.765]	[0.665]
$\Delta\left(\ln \frac{L^M}{L^L}\right)_{o,\tau}$		0.470	0.553		0.478	0.560	0.571	
		[0.167]***	[.]		[0.167]***	[.]	[.]	
$\Delta\left(w^M - w^L\right)_{o,\tau}$		6.28e-06	-4.47e-05		8.37e-06	-4.19e-05		
		[0.000]	[0.000]*		[0.000]	[0.000]		
$\Delta GDPPC_{o,\tau}$			0.0608			0.0600	0.0513	
			[0.012]***			[0.012]***	[0.005]***	
$\Delta GINI_{o,\tau}$							-0.523	
							[0.292]*	
R-squared	0.008	0.031	0.058	0.005	0.028	0.055	0.054	0.168
F-Stats				48.54	45.73	45.51	45.45	47.26
Observations	2,166	1,776	1,776	2,166	1,776	1,776	1,776	2,166

Notes: ***, **, *, denote statistical significance at the 1%, 5% and 10% level, respectively. Robust standard errors (clustered by Canton and origin country) are given in parentheses. All models include fixed effects for Cantons, origin countries and decades. Regressions are weighted using the total number of recent immigrants from origin country o in destination j at the beginning of the decade as weight. $RSH_{j,t}$ is instrumented with $\widetilde{RSH}_{j,1970}$. $\Delta\left(\ln \frac{L^H}{L^M}\right)_{o,\tau}$ and $\Delta\left(\ln \frac{L^M}{L^L}\right)_{o,\tau}$ is the change in the log relative number of high to middle or middle to low educated workers in origin country o and decade τ, respectively. $\Delta\left(w^M - w^L\right)_{o,\tau}$ and $\Delta\left(w^M - w^L\right)_{o,\tau}$ are the decennial change in the wage differential between highly and middle and middle and low educated workers in origin country o and decade τ, respectively. τ. $\Delta GDPPC_{o,\tau}$ and $\Delta GINI_{o,\tau}$ represent the decennial change in GDP per capita and the Gini index in origin country o and decade τ. See section 3.3.1 for a more detailed description of variables.

Table A.7: Determinants of the Change in Education Group Shares of Recent Immigrants, 1980 - 2010, Weighted with Total Workforce, OLS and 2SLS Estimates

	OLS			2SLS				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Dependent Variable: Change of High Skill Labour Share								
$RSH_{j,t}$	-0.00766	0.0279	0.0307	0.367	0.355	0.365	0.365	0.379
	[0.128]	[0.106]	[0.106]	[0.097]***	[0.129]***	[0.130]***	[0.131]***	[0.096]***
$\Delta EDUSH^{H}_{o,\tau}$		0.771	0.704		0.771	0.704	0.715	
		[0.278]***	[0.219]***		[0.277]***	[0.217]***	[0.229]***	
$\Delta\left(w^{H}-w^{M}\right)_{o,\tau}$		-2.22e-06	-4.87e-06		-2.17e-06	-4.83e-06		
		[0.000]	[0.000]***		[0.000]	[0.000]***		
$\Delta GDPPC_{o,\tau}$			0.0105			0.0105	0.00825	
			[0.004]***			[0.004]***	[0.003]**	
$\Delta GINI_{o,\tau}$							-0.189	
							[0.063]***	
R-squared	0.000	0.007	0.012	-0.003	0.004	0.010	0.010	0.102
F-Stats				33.07	38.54	38.48	38.52	31.97
B. Dependent Variable: Change of Middle Skill Labour Share								
$RSH_{j,t}$	-0.194	-0.135	-0.135	-0.457	-0.330	-0.328	-0.329	-0.448
	[0.100]*	[0.120]	[0.121]	[0.097]***	[0.139]**	[0.139]**	[0.140]**	[0.080]***
$\Delta EDUSH^{M}_{o,\tau}$		0.420	0.418		0.419	0.417	0.362	
		[0.197]**	[0.196]**		[0.196]**	[0.196]**	[0.176]**	
$\Delta\left(w^{H}-w^{M}\right)_{o,\tau}$		3.17e-06	3.37e-06		3.18e-06	3.38e-06		
		[0.000]	[0.000]		[0.000]	[0.000]		
$\Delta\left(w^{M}-w^{L}\right)_{o,\tau}$		4.83e-06	2.37e-06		4.69e-06	2.24e-06		
		[0.000]	[0.000]		[0.000]	[0.000]		
$\Delta GDPPC_{o,\tau}$			0.00211			0.00211	0.00414	
			[0.004]			[0.004]	[0.003]	
$\Delta GINI_{o,\tau}$							0.182	
							[0.116]	
R-squared	0.001	0.010	0.010	-0.001	0.009	0.009	0.011	0.056
F-Stats				33.07	38.56	38.51	38.56	31.97
C. Dependent Variable: Change of Low Skill Labour Share								
$RSH_{j,t}$	0.202	0.105	0.105	0.0898	-0.0300	-0.0405	-0.0401	0.0697
	[0.077]***	[0.056]*	[0.058]*	[0.086]	[0.117]	[0.116]	[0.116]	[0.087]
$\Delta EDUSH^{L}_{o,\tau}$		0.378	0.371		0.378	0.371	0.367	
		[0.073]***	[0.048]***		[0.073]***	[0.046]***	[0.034]***	
$\Delta\left(w^{M}-w^{L}\right)_{o,\tau}$		-1.20e-05	7.57e-07		-1.21e-05	6.80e-07		
		[0.000]	[0.000]		[0.000]	[0.000]		
$\Delta GDPPC_{o,\tau}$			-0.0133			-0.0133	-0.0130	
			[0.004]***			[0.004]***	[0.004]***	
$\Delta GINI_{o,\tau}$							-0.00713	
							[0.068]	
R-squared	0.001	0.014	0.027	0.001	0.013	0.026	0.026	0.125
F-Stats				33.07	38.59	38.53	38.54	31.97
Observations	4,144	2,987	2,987	4,144	2,987	2,987	2,987	4,144

Notes: ***, **, *, denote statistical significance at the 1%, 5% and 10% level, respectively. Robust standard errors (clustered by Canton and origin country) are given in parentheses. All models include fixed effects for Cantons, origin countries and decades. Regressions are weighted using the total number of recent immigrants from origin country o in destination j at the beginning of the decade as weight. $RSH_{j,t}$ is instrumented with $\widetilde{RSH}_{j,1970}$. $\Delta EDUSH^{E}_{o,\tau}$ is the decennial change in the share of education group $E \in \{H, M, L\}$ in origin country o and decade $\Delta\left(w^{M}-w^{L}\right)_{o,\tau}$ and $\Delta\left(w^{M}-w^{L}\right)_{o,\tau}$ are the decennial change in the wage differential between highly and middle and middle and low educated workers in origin country o and decade τ, respectively. τ. $\Delta GDPPC_{o,\tau}$ and $\Delta GINI_{o,\tau}$ represent the decennial change in GDP per capita and the Gini index in origin country o and decade τ. See section 3.3.1 for a more detailed description of variables.

Table A.8: Determinants of the Change in Education Group Shares of Recent Immigrants, 1980 - 2010, Empty Cells Treated as Missing, OLS and 2SLS Estimates

	OLS			2SLS				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	A. Dependent Variable: Change of High Skill Labour Share							
$RSH_{j,t}$	0.176	0.214	0.188	0.387	0.419	0.396	0.399	0.354
	[0.053]***	[0.079]***	[0.079]**	[0.130]***	[0.136]***	[0.139]***	[0.139]***	[0.114]***
$\Delta EDUSH^H_{o,\tau}$		1.318	1.065		1.308	1.057	1.085	
		[0.380]***	[0.180]***		[0.377]***	[0.175]***	[0.216]***	
$\Delta\left(w^H - w^M\right)_{o,\tau}$		-4.87e-07	-3.36e-06		-2.94e-07	-3.14e-06		
		[0.000]	[0.000]**		[0.000]	[0.000]**		
$\Delta GDPPC_{o,\tau}$			0.0150			0.0149	0.0135	
			[0.003]***			[0.003]***	[0.003]***	
$\Delta GINI_{o,\tau}$							-0.117	
							[0.084]	
R-squared	0.004	0.085	0.173	-0.002	0.080	0.168	0.165	0.359
F-Stats				40.41	39.23	39.03	38.95	38.90
	B. Dependent Variable: Change of Middle Skill Labour Share							
$RSH_{j,t}$	-0.348	-0.334	-0.338	-0.381	-0.413	-0.416	-0.419	-0.368
	[0.106]***	[0.113]***	[0.115]***	[0.138]***	[0.132]***	[0.132]***	[0.133]***	[0.123]***
$\Delta EDUSH^M_{o,\tau}$		1.066	1.077		1.061	1.073	0.973	
		[0.258]***	[0.259]***		[0.259]***	[0.261]***	[0.239]***	
$\Delta\left(w^H - w^M\right)_{o,\tau}$		-4.54e-06	-4.44e-06		-4.58e-06	-4.47e-06		
		[0.000]*	[0.000]*		[0.000]*	[0.000]*		
$\Delta\left(w^M - w^L\right)_{o,\tau}$		2.20e-05	2.03e-05		2.19e-05	2.01e-05		
		[0.000]***	[0.000]**		[0.000]***	[0.000]***		
$\Delta GDPPC_{o,\tau}$			0.00172			0.00177	0.00403	
			[0.002]			[0.002]	[0.001]***	
$\Delta GINI_{o,\tau}$							0.0697	
							[0.053]	
R-squared	0.017	0.134	0.135	0.017	0.133	0.135	0.121	0.269
F-Stats				40.41	39.08	38.89	38.86	38.90
	C. Dependent Variable: Change of Low Skill Labour Share							
$RSH_{j,t}$	0.172	0.110	0.154	-0.00592	-0.0164	0.0191	0.0182	0.0131
	[0.118]	[0.111]	[0.110]	[0.114]	[0.124]	[0.123]	[0.121]	[0.113]
$\Delta EDUSH^L_{o,\tau}$		0.690	0.736		0.694	0.740	0.741	
		[0.238]***	[0.161]***		[0.235]***	[0.154]***	[0.148]***	
$\Delta\left(w^M - w^L\right)_{o,\tau}$		-1.31e-05	2.13e-06		-1.33e-05	1.73e-06		
		[0.000]	[0.000]		[0.000]	[0.000]		
$\Delta GDPPC_{o,\tau}$			-0.0184			-0.0183	-0.0179	
			[0.002]***			[0.002]***	[0.000]***	
$\Delta GINI_{o,\tau}$							0.0172	
							[0.069]	
R-squared	0.004	0.108	0.257	-0.000	0.105	0.254	0.254	0.333
F-Stats				40.41	39.11	38.90	38.86	38.90
Observations	1,738	1,394	1,394	1,738	1,394	1,394	1,394	1,738

Notes: ***, **, *, denote statistical significance at the 1%, 5% and 10% level, respectively. Robust standard errors (clustered by Canton and origin country) are given in parentheses. All models include fixed effects for Cantons, origin countries and decades. Regressions are weighted using the total number of recent immigrants from origin country o in destination j at the beginning of the decade as weight. $RSH_{j,t}$ is instrumented with $\widetilde{RSH}_{j,1970}$. $\Delta EDUSH^E_{o,\tau}$ is the decennial change in the share of education group $E \in \{H, M, L\}$ in origin country o and decade $\Delta\left(w^M - w^L\right)_{o,\tau}$ and $\Delta\left(w^M - w^L\right)_{o,\tau}$ are the decennial change in the wage differential between highly and middle and middle and low educated workers in origin country o and decade τ, respectively. τ. $\Delta GDPPC_{o,\tau}$ and $\Delta GINI_{o,\tau}$ represent the decennial change in GDP per capita and the Gini index in origin country o and decade τ. See section 3.3.1 for a more detailed description of variables.

3.B Data Appendix

3.B.1 Measuring Employment

We measure labour supply in full time equivalents (FTEs) based on weekly hours worked. For the 1970, 1980, 1990 and 2000 censuses, however, only the following 4 categories were available for weekly hours worked instead of exact hours. We therefore used the 1991 Swiss Labour Survey (Schweizerische Arbeitskräfteerhebung, SAKE) which contains the same 4 categories but also the actual hours worked in order to arrive at the following weighting scheme.

- 1-5 hours per week: 0.05 FTEs
- 6-24 hours per week: 0.35 FTEs
- 25-41 hours per week: 0.7 FTEs
- 42 or more hours per week: 1 FTEs

In the 2010 census on the other hand, weekly hours were exactly measured. We divided them by 42 which corresponds to a full time working week measured in hours. Hours above 42 were capped, i.e. an individual working more than 42 hours per week was counted as one full time equivalent. Since the new census is conducted as a representative sample, individuals were then weighted according to the official weights contained in the data.

3.B.2 Distinguishing Recent and Early Immigrants from Natives

In the censuses 1970-2000, we used the country of birth and the country of residence 5 years prior the census to distinguish amongst natives, early and recent immigrants. An individual having Switzerland as its country of permanent residence 5 years previous to the census date and Switzerland as its country of birth was counted as *native*. An individual having Switzerland as its residence 5 years previous to the census but another country as country of birth was counted as an *early immigrant*. An individual living in another country 5 years prior to the census was counted as an *recent immigrant* (regardless of its birth country, i.e. a Swiss-born individual living abroad and then reentering Switzerland was counted as a recent immigrant. Results are robust if we consider those individuals as natives).

In the 2010 census, the residence permit can be used as an additional variable to distinguish between early and recent immigrants and native workers. This allows to fill in some missing values that would have appeared if we used only the year of arrival to distinguish between early and recent immigrants. Individuals holding a permit of class L, B and F were also counted as recent immigrants in case they had not already by our previous definition. Individuals with permits C and Ci were counted as early immigrants if they had not already.

3.B.3 Distinguishing Education Groups

We classify workers into three education groups using the International Standard Classification of Education (ISCED) following Peri (2005). A *highly educated* worker as corresponds to those holding a tertiary degree (ISCED 5 and 6). A *middle educated worker* holds a degree from a secondary school (ISCED 3 and 4) whereas a *low educated* worker only has finished compulsory education (ISCED 0, 1 and 2) or did not finish school.

3.B.4 Defining Occupations

The Swiss Census contains two classifications of occupations for all survey years. The ISCO-88-COM is a version of the ISCO-88 and internationally comparable in principle. The Swiss Nomenclature of Occupations 2000 (SNO-2000) is a national classification scheme not comparable to those of other countries. However, it is straightforward to map it to the ISCO-88 or to US occupation classifications.

In case of the ISCO-88-COM, about a third of the two-digit ISCO-classes contain no observations prior to 2010 and about half of two-digit classes are missing prior to 1990. This makes it impossible to keep track of the two-digit-classes in detail. Furthermore, some of the occupations show an implausibly volatile development in recent years, in particular ISCO no. 93, which jumps from less than 90'000 in 1980 to over 430'000 in 1990 and then falls again to less than 20'000 in 2000. According to the Statistical Office of Switzerland, ISCO no. 93 contains a vast number of employees (especially in 1990) which could not be appropriately allocated to the ISCO-classification and thus were assigned to the broad class ISCO no. 93. However, one-digit ISCO-classes seem to yield plausible results and can be used to check our descriptive results (where ISCO 93 must be excluded from the analysis).

Contrary to the ISCO-88-COM, the SBN-2000 has entries in almost all of the two-digit classes for every survey year. Due to this fairly complete picture and the existence of reliable and complete keys, we are able to map the SNO-2000 occupations into the ISCO-88-COM by two steps. First, we mapped the SNO-2000 to the older SNO-1990 [49] and then,

[49] In principle, the crosswalk SNO-2000 / SNO-1990 only allows for a complete matching from SNO-1990 to SNO-2000 occupations but not the other way round. However, since the mapping in almost

using another crosswalk and thereby following Basten and Siegenthaler (2013), mapped those classes into the ISCO-88-COM. This procedure resulted in 26 two-digit ISCO-88-COM classes with no missing entries and, in particular, implausibly volatile occupation classes do not occur anymore. However, similar to the ISCO-classification, the SNO-2000 contains one extraordinary volatile class, namely SNO-2000 no. 93, whose inclusion would yield to seriously distorted labour-shares for the other occupations. SNO 93 along with SNO 92 explicitly contain occupations which could not be classified by the statistical agency. Hence we excluded SNO 92 along with SNO 93 from the analysis.

Albeit we have to take into account that the constructed ISCO-88-COM classes may introduce some inaccuracy, it gives us the possibility to work with about 26 ISCO-classes instead of only 1-digit-ISCOs contained in the censuses. The resulting occupations exhibit a plausible development over the years and the results obtained in our paper fit nicely into the results found by the literature for other countries.

3.B.5 Offshorability

We obtain offshorability measures from two sources. Using several hundred cases of offshoring in Europe, Goos et al. (2011) construct an index of how offshorable an occupation is (see Table 4 in Goos et al., 2011). As they work with two-digit-ISCOs, we can directly map those indices to our dataset. Blinder and Krueger (2013) on the other hand, report survey measurements of offshorability for US occupations, industries and various personal characteristics of their dataset such as offshorability by education level. Matching the latter to our dataset proved again straightforward as similar educational attainment measures were contained in the Swiss census. From these offshorability measures by occupations and educational levels, we compute offshorability indices for each commuting zone in Switzerland in the following ways:

$$OFFSH^{occ}_{j,t} = \sum_k \frac{L_{j,t,k}}{L_{j,t}} OFFSH_{t,k}$$

$$OFFSH^{skill}_{j,t} = \sum_e \frac{L_{j,t,e}}{L_{j,t}} OFFSH_{t,e}$$

where $OFFSH_{t,k}$ is the offshorability measures for occupations from Goos et al. (2011). And $OFFSH_{t,e}$ are the offshorability measures for skill groups *high*, *middle* and *low*, computed by using the indices provided by Blinder and Krueger (2013) for 6 different educational attainments.

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all cases is a 1-to-1 mapping, almost no occupations get lost (i.e. classified missing) if one maps the SNO-2000 to SNO-1990.

4 Demand Forces of Technical Change Evidence from the Chinese Manufacturing Industry

Joint with Franziska Weiss, Josef Zweimüller and Fabrizio Zilibotti

4.1 Introduction

To which extent does the emerging middle class fuel growth and technical change in the Chinese manufacturing industries? The unprecedented growth in average incomes in China since the outset of its economic reforms in 1978 lifted over half a billion people out of poverty. The process was associated with the emergence of a new class of consumers with discretionary income to spend on consumer goods that satisfy less basic needs. This paper asks whether and to which extent the expected expansion of the local market for consumer durables might have stimulated productivity-enhancing investments by Chinese firms, thus partly contributing to an explanation of the surge of technical progress in Chinese manufacturing.

Our empirical investigation is motivated by recent theories of growth with directed technical change (e.g., Acemoglu and Zilibotti (2001), Acemoglu (2002), henceforth DTC) and with non-homothetic preferences (Foellmi and Zweimüller (2006), Boppart (2014), henceforth NHP). The theory of DTC predicates that firms' investments in new technologies hinge on a market size effect: as the demand for a good produced by a particular industry increases, firms in such an industry invest more in the creation or adoption of new technologies relative to industries in which demand is sluggish. The theory of NHP predicts, in turn, that economic growth affects the sectoral composition of domestic demand. It is well-known, for instance, that economic development and the formation of a middle class reduces the food share of consumption and stimulates the demand of durable consumption goods. If, in addition, there is a hierarchy in the consumers' purchase of durable good (e.g., as they grow richer, households purchase first a motorbike, and then a car) the process of economic growth is characterized by waves of expansion of the domestic market for different durable goods. Merging the insight of the two theories yields the prediction that economic growth brings about demand-driven waves of technical progress: the expectation of a future market size expansion for the product of a particular industry causes a boom in innovative activities in that industry.[1]

To establish an empirical link between expected market size and technical progress, we combine data from two different sources: the Chinese Health and Nutrition Survey (CHNS) which provides information on consumption behavior of households; and the Annual Survey of Industrial Production (ASIP) from which firm-specific productivity measures (and their changes over time) can be calculated. We concentrate on 16 industries covering a substantial share of expenditures for consumer durables: cellphones, cars, computers, telephones, refrigerators, home video appliances, washing machines, air conditioning, cameras, satellite dishes, motorcycles, kitchen appliances, radios, sewing machines, electric fans and cycles.

A potential problem with our empirical analysis is the endogeneity of market size. Technical progress can be the trigger rather than the effect of the expansion in the domestic market of a specific product, e.g., by causing a fall in its sale price. To tackle the endogeneity problem we exploit the large variation in the households' distribution across income classes associated with the Chinese economic growth during the last two decades: in 1990 less than one percent of Chinese households fell into the category of high-middle income and high-income households, while both low-income and low-middle income households made up close to 50 percent each.[2] By the year 2009, the fraction of low-income and low-middle income households has fallen below 10 percent and to 40 percent, respectively, while the fraction of high-middle and high-income households has increased to more than 30 percent and 20 percent, respectively. These changes lead to predictable, differential changes in demand across various consumer goods industries. For instance, to return to the previous example, the market for motorcycles booms earlier than the market for cars. However, at some point, the former becomes saturated, and the potential for future market expansion dies off. At that point, it is the car industry that starts attracting investments and innovative activities. It is this source of variation that forms the basis of our strategy to identify the impact of expected demand on technical change in Chinese manufacturing industries.

More precisely, we construct product-specific Engel-curves for the 16 consumer durables, and estimate changes in expected market size for each durable good. We first fix income-

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[1] A formal argument of the link between DTC and NHP is provided in the recent theory of structural change of Boppart and Weiss (2013)

[2] Following World Bank convention, we group households into four classes: low-income, low-middle income, high-middle income, and high-income. The corresponding income brackets – measured in real incomes per year in constant 2009 Yuan - are: 0-2'149 Yuan; 2'150-8'514 Yuan; 8'515-16'499 Yuan; and 16'500 Yuan or more. (Measured in 2009 US $ this corresponds to US $ 0-2'149; US $ 2'150-4'167; US $ 4'168-8'075; and US $ 8076 or more.)

group specific ownership rates of a particular durable good to a particular base-year and then use the changing population shares across income classes to calculate a measure of potential ownership and potential market size in other years. This yields an industry-specific markets size measure, whose evolution over time is entirely driven by changes in the income distribution. Changes in ownership patterns of a given income group, which might be induced by changes in prices or the quality of goods, do not affect this potential market size measure. To the extent that these differential changes in expected markets size are uncorrelated with unobserved factors that drive innovation incentives, our market size measure identifies the impact of expected demand on technical change in Chinese manufacturing.

We find quantitatively important demand effects on technical change: a one percent increase in expected market size increases firm-specific TFP by 0.27% and firm-specific labor productivity by 0.42%. Hence our findings suggest that firms in industries with a large expected local market are significantly more productive today, and show higher levels of other measures of innovative activity. Moreover, the effect of expected market size becomes larger when the expected market size measure is constructed from a longer time window over which firms may form expectations about local market size.

The estimated effect of expected market size is robust to a number of checks. First, we include a rich set of firm-level determinants of R&D and market concentrations, in particular foreign and government ownership, as some scholars pointed out that this may affect productivity to a considerable degree (Van Reenen and Yueh, 2012). Second, we show that our results are robust to supply-side drivers of R&D affecting innovation opportunities of Chinese firms by including a measure of worldwide technology potential reported by Swiss firms. Third, our findings our robust when we control for a firms' export status. This is particularly important in the context of China, as the Chinese economy is strongly export-driven, so demand conditions on export markets may be more relevant for productivity and technical progress than domestic demand. We test for the robustness of our results controlling for firms' export behavior. Interestingly, in our dataset there is a stark dichotomy between exporting and non-exporting firms. About 50% of the firms in our sample do not export at all, whereas for 24% of them exports account for more than 75% of their total sales.[3] Interestingly, we find that the domestic market size effect is totally insignificant for exporting firms. Instead, our results are driven entirely by non-exporting firms serving exclusively the Chinese market. This is coherent with our hypothesis that innovative activity is driven by the expectations of future market size. For exporting firms what matters is the global market, thus the expansion of the

[3]To be precise, it may be that one firm exports in one year but not in the next year. Shares are taken with respect to the panel of data points.

domestic market size is less important. It is instead the technology adoption behavior of non-exporting firms that hinges the most on the expectation of about future domestic demand. For instance, the incentive for a Chinese car producer serving the local market to invest in technology hinges on the expansion of the Chinese middle class. In contrast, this does not matter for an assembling firm producing cameras that are exported to the West.

Empirical studies thoroughly examining the effect of market size on innovation remain relatively scarce with most papers focusing on the pharmaceutical industry. Acemoglu and Linn (2004) document a causal link between market size and innovation building on differential patterns of drug use between young and old individuals. Exploiting the demographic changes in the U.S. population as exogenous source of variation in market size, they find a positive effect of expected demand on innovation across different drug categories. Their findings are quantitatively important and very robust. A one percent increase in potential market size leads to approximately a 4% increase in the entry of new non-generic drugs. Finkelstein (2004) demonstrates that health policies designed to increase utilization of vaccines created strong incentives to develop new vaccines. According to her estimates, a 1 dollar increase in expected annual revenue for vaccines generates additional 6 cents of investment in that vaccine. Moreover, these policies were associated with a 2.5-fold increase in clinical trials for new vaccines. Contrasting evidence comes from Acemoglu et al. (2006) who investigate the effect of Medicare on the development of new pharmaceuticals for the elderly. They find no evidence that the introduction of Medicare is associated with an increase in drug consumption among the elderly. Consistent with this, they also find no evidence of an increase in the approval of new drugs more likely to treat diseases that affect the elderly, after Medicare's introduction. Blume-Kohout and Sood (2013) consider the market size increase for prescription drugs through Medicare Part D which increased pharmaceutical firms' expected sales. They find a significant increase in pharmaceutical R&D for therapeutic classes with a higher Medicare market share. De Mouzon et al. (2011) use detailed data on spending patterns of patients (and their insurers) to show that expected market size has a highly significant and quantitatively important effect on innovations (as measured by the number of new chemical entities of the market of a particular disease class.)

The above findings all indicate a large impact of expected market size on innovative activities but they are specific to the pharmaceutical industry. It is not clear whether empirical evidence from the pharmaceutical industry applies to other industries as well. The recent study by Boppart and Weiss (2013) focuses on demand effects on R&D in the whole U.S. industry. Using the input-output structure of different industries as an instrument for actual market size, it turns out that a sector's market share has a significant positive effect on sector-specific R&D investments.

Our paper is also related to the literature studying the determinants of the recent sharp increase in R&D and patent activity in China. The share of R&D expenditure on GDP roughly tripled in China from 0.6% in 1996 to over 1.8% in 2011 (World Bank, 2014). While an increase in R&D intensity is a common pattern over the development process, this has started when China has still a very large technology gap from the frontier. Taiwan, for comparison, reached the same R&D-to-GDP ratio in 1995 as did China in 2009, when its GDP per capita was twice as large as China in 2009. Some recent studies argue that this exceptional pattern is partly due to the opportunities provided by the presence of a large domestic market. Gao and Jefferson (2007) argue that large and fast growing consumer markets create a premium for research-intensive industries to establish production centers in close proximity to burgeoning-consumer markets. Hu and Jefferson (2009) go further and suggest that an important driving force could be the changing composition of domestic consumption shifting away from products with low-technology content (such as bicycles) to goods and services that are more technology intensive (such as automobiles).

The rest of the paper is organized as follows. Section 2 describes our data sources and provides some descriptive statistics. Section 3 explains the econometric model and lays out our empirical strategy. Section 4 presents the baseline results and section 5 discusses a variety of robustness checks. Finally, section 5 concludes.

4.2 Data and Descriptive Statistics

We use two micro-level data sources. The first contains household-level data about the ownership of durable goods to construct a count measure of actual market size.[4] The second contains firm-level manufacturing data about value added, investments and employment that we used to estimate total factor productivity, our main outcome measure of innovative investments.

[4]Working with durable goods ownership rather than household expenditure data has some important advantages but also bears some difficulties. The main advantage is that CHNS' coverage of a relatively broad set of different durable goods allows to construct a market size measure with substantial industry and time variation which can be linked relatively straightforward to different industries in the manufacturing data. Second, the lumpy nature of durable goods creates an interesting variation in ownership profiles across the income distribution which can be exploited to create an exogenous measure of market size. As a major disadvantage relative to expenditure data, we have no information about the value of different durable goods. Therefore, we can only use the population count of each durable good in the population and need to abstract from value weighted market size measure. See appendix 4.B.1 for more details.

4.2.1 Market Size

The household-level ownership data are from the China Health and Nutrition Survey (CHNS). The CHNS was collected in eight waves between 1989 to 2009, and covers a representative sample of Chinese urban and rural households across nine provinces with substantial variation in geography, economic development and public resources. These data are publicly available and are widely used in the literature.[5] The CHNS contains information, for a number of durable goods, on how many items of a particular durable good are owned by each household, of which we also know the income and household size. We combine this information with the size of the Chinese population to estimate total number of items of a particular durable good j held by Chinese consumers in year t, denoted by $Stock^{actual}_{j,t}$.[6]

Figure 4.1 shows the diffusion patterns of five selected durable goods between 1989 to 2009: cycles, electric fan, refrigerator, air condition, and car. The years not covered by the CHNS are fitted by linear interpolation.[7] The time interval between 1998 and 2007, which we can match to the firm-level data described below, is marked with the dotted vertical lines. Electrical fans were already widespread in the early years, and feature some saturation in more recent years. Saturation is even stronger for bicycles whose stock is decreasing since 2000, likely to be due to their progressive substitution with higher-ranked transportation vehicles such as motorcycles and cars. There is no saturation for refrigerators, air conditioning and cars. The ownership of these durables is booming during the period of our study.

We use the evolution of the ownership stock to infer the flow of newly purchased goods, our proxy for market size. To calculate such a flow we take into account that the per capita stock of each durable good can change for three reasons: (i) some households acquire the good for the first time (extensive margin); (ii) some households who already own units of the good buy additional units (intensive margin); (iii) some households replace worn out items (replacement demand). Assuming a constant replacement rate δ_j yields the following annual flow of newly purchased goods (*actual market size*):

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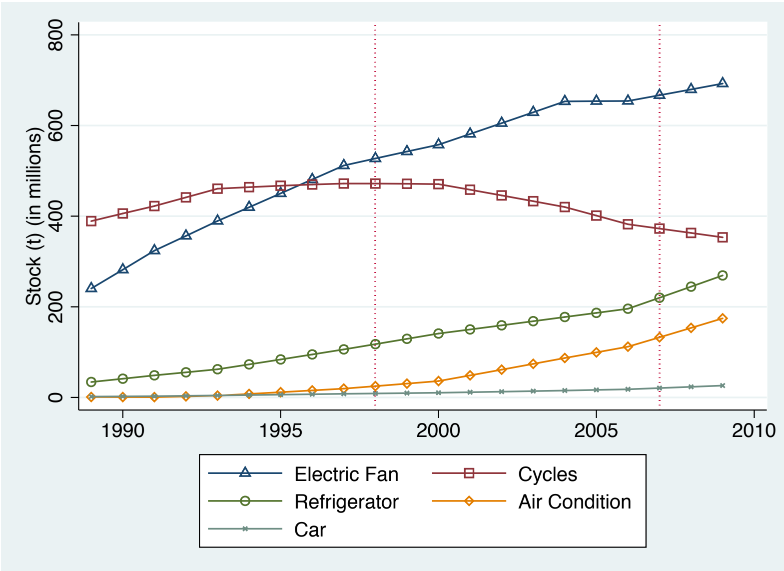
[5]See, among others, Benjamin et al. (2005a), Benjamin et al. (2005b), Liu (2008). See Beerli (2010) for a more detailed description of this data set.

[6]The population of China is from the Penn World Tables. More formally, we use the number of items of a specific durable good j in wave t owned by household h, $nrowned_{h,t}$, and the number of household members, $hhsize_{h,t}$, to compute the average number of items per head, i.e. $\left[\frac{1}{H_t}\sum_{h=1}^{H_t}\left(\frac{nrowned_{h,t}}{hhsize_{h,t}}\right)\right]$, where H_t is total number of households in period t. Then, we take the Chinese population size in year t (China Version 1) from the Penn World Tables 7.1, Heston et al. (2011), to get $Stock^{actual}_{j,t}$.

[7]"Cycles" are the cumulative ownership of bicycles and tricycles. See section 4.2.2 for details.

Figure 4.1: Evolution of Durable Good Stocks



Notes: The figure shows the total items owned (in millions) for each durable good, $Stock^{actual}_{j,t}$, i.e. for electric fans, refrigerators, air conditioners and cars. "Cycles" is the cumulative ownership of bicycles and tricycles. CHNS data 1989 to 2009, years between survey waves linearly interpolated.

$$MS^{actual}_{j,t,t+1} = \underbrace{\left[Stock^{actual}_{j,t+1} - Stock^{actual}_{j,t}\right]}_{\text{new purchases}} + \underbrace{\delta_j \cdot Stock^{actual}_{j,t}}_{\text{replacement purchases}}$$

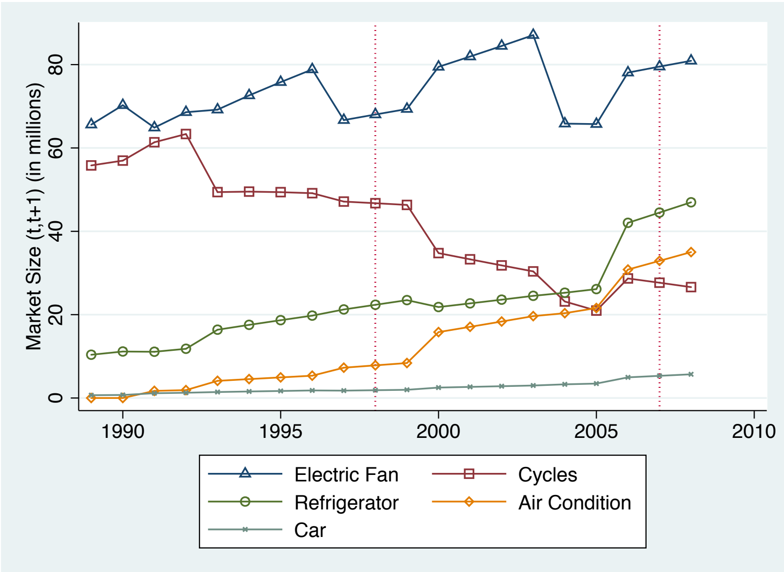
Unfortunately, the CHNS provides no information about when households decide to scrap existing durable goods. Nor could we find estimates of depreciation of durables for China. We resort to using the depreciation estimates available for the US from the Bureau of Economic Analysis (2003). As shown in appendix table A.1, the Bureau of Economic Analysis (2003) offers depreciation estimates for a large variety of different durable goods for the years 1925 to 1995.[8] We use the average over this long period. We check the robustness of the results to using alternative depreciation rates. The results are robust to a large range of depreciation rates. When the estimate of $MS^{actual}_{j,t,t+1}$ so calculated is smaller than one, we set $MS^{actual}_{j,t,t+1}$ to one.[9]

[8] The Bureau of Economic Analysis (2003) estimates the length of service lives (in years) for a large variety of durable goods for years 1925 and 1997. By definition, assets are "retired" from the stock at the end of their service lives. Following the Bureau of Economic Analysis (2003), we set δ_j equal to the inverse of the service life of a durable good j. This represents the share of the total stock of a durable, which needs to be replaced each year, in order to keep the total stock constant.

[9] While this adjustment is somewhat arbitrary, we prefer this route to eliminating negative observations from the sample, as the latter would cause a major selection problem. In the case of negative growth, we

Figure 4.2 displays the evolution of market size for the five durable goods displayed in figure 4.1. The electric fan market is stationary; the market for cycles is shrinking; finally the market for refrigerators, air conditioning and cars is increasing.

Figure 4.2: Evolution of Market Size of Durable Goods



Notes: Actual market size is constructed as explained in the text, i.e. $MS^{actual}_{j,t,t+1} = \left[Stock^{actual}_{j,t+1} - Stock^{actual}_{j,t}\right] + \delta_j \cdot Stock^{actual}_{j,t}$ where estimates for δ_j are taken from the BEA (2003). CHNS data 1989 to 2009.

In our regression analysis below, we use market size over a multi-period horizon. More formally, our market size measure is the yearly average over the relevant period (e.g., $k = 4$ means a five-year horizon taking into account the stock of goods between t and $t + 4$):

$$MS^{actual}_{j,t,t+k} = \frac{1}{k} \sum_{s=0}^{k-1} \left[MS^{actual}_{j,t+s,t+s+1}\right].$$

4.2.2 Industrial Production

We use firm-level data from the Annual Survey of Industrial Production (ASIP) 1998-2007. The survey is conducted by the Chinese government's National Bureau of Statistics (NBS).

set MS^{actual} to unity rather than to zero because in the regression analysis below we take the logarithm of MS^{actual} and this is not defined at zero. To keep the ranking of goods unchanged, this then requires us to set all observations between zero and one to one. Note that this adjustment only concerns two observations of $MS^{actual}_{j,t,t+1}$ of radios in 2004 and 2005. However, in our baseline regressions these two observations are not included as we are interested in the market size effect over a longer time horizon, i.e. $MS^{actual}_{j,t,t+4}$.

The ASIP is a census of all non-state firms with more than 5 million RMB in revenue (about $800,000 at the current exchange rate) plus all state-owned firms in manufacturing. The raw data consists of over 150,000 firms in 1998 and grows to over 300'000 firms in 2007. The ASIP covers a wide range of information about the firm's balance sheet, cash-flow and ownership which provides us with a rich set of control variables. This data set has been used extensively in the recent literature.[10]

We estimate total factor productivity (TFP) at the firm-level using data on value added, the stock of fixed assets, intermediate inputs and employment applying the estimation procedure suggested by Levinsohn and Petrin (2003) to account for the endogeneity of factor input choices.[11] We take TFP as a proxy for the investment in innovation.[12] We check the robustness of our results by using labor productivity as a second measure of innovation activities. This is sometimes preferred to TFP in the literature, due to its superior stability (see also Crépon et al. (1998)). The most natural measure of innovation however, would be R&D expenditure. But unfortunately, we cannot use this measure as it is only available for the years 2005 to 2007.

We link each durable good observed in the CHNS to the four digit manufacturing industry producing it as a final household consumption good according to the NBS (2008) description of the Chinese Industry Classification (CIC) system. A limitation of this approach is that it neglects those industries which produce the durable goods as equipment or intermediate inputs (as opposed to final goods) for other industries – this is however quantitatively not very important for the durable goods we consider. We collapse the 22 categories of durable goods available from the CHNS into 16 manufacturing industries, as in some cases different durable goods are produced by firms belonging in the same four-digit manufacturing industry.[13] Following Brandt et al. (2012) we exclude all firms with less then 8 employees and those with negative values of value added and capital stock.[14] Additionally, as noted by Feenstra et al. (2014), the NBS data are fairly noisy due to mis-reporting and other sources of measurement error. Since measurement error is

[10] A detailed description of the data set can be found in Brandt et al. (2012). Other recent papers include, for instance, Feenstra et al. (2014) and Hsieh and Klenow (2009).

[11] The estimation of total factor productivity is explained in greater detail in data appendix 4.B.2.

[12] Using TFP as a proxy for innovative investments is common in the literature. See among others, Crépon et al. (1998) or Acemoglu et al. (2010).

[13] Since color TVs and DVD players are produced by the same four-digit manufacturing industries, we created a new ownership variable for home video appliances which is simply the cumulative ownership of those two goods irrespectively whether this is a color TV or a DVD player. We proceed in a similar fashion in the case of the kitchen appliance industry as the cumulative of microwaves, rice cookers and pressure cookers and in the case of the cycle industry being the cumulative of bicycles and tricycles. The exact list of durable goods and matched industries can be found in table A.3 in the data appendix.

[14] We also employ their procedure to link restructured firms over time, cf. the online appendix of Brandt et al. (2012) for more details.

likely to be larger among very small (e.g. family-managed) firms, which do not set up a formal accounting system, we exclude the smallest 10% of firms in terms of value added (on a yearly basis).[15] We end up with a final sample of 30'883 firm observations in 16 durable good industries over the years 1998–2007.

4.3 Empirical Strategy

4.3.1 Econometric Model

To study the effect of market size on innovation we consider the following regression model

$$\ln Y_{i,j,t} = \alpha\left(\ln MS^{actual}_{j,t,t+4}\right) + \mathbf{X}'_{i,j,t}\beta + \psi HHI_{j,t} + \eta_j + \lambda_t + \epsilon_{i,j,t},$$

where i denotes a firm, j an industry (durable good) and t the time. The main goal is to estimate the effect of the future market size at the industry level, $MS^{actual}_{j,t,t+4}$, on the firm-level measure of innovation activity, $Y_{i,j,t}$. $MS^{actual}_{j,t,t+4}$ measures the annual average change in the total number of items of a durable good j between t and $t+4$ adjusted for depreciation, as discussed above. The five-year window benchmark is similar as in Acemoglu and Linn (2004), as this is a plausible time horizon to determine firms' investments in innovation. Our main outcome variable is TFP, a proxy for the firm-level investment in technology adoption. We perform robustness analysis using alternative proxies for innovation such as labor productivity, as well as alternative windows for future market size.[16]

In all specifications, we include industry fixed effects, η_j, to account for industry-specific innovation intensities (e.g., the car industry is inherently more technology-intensive than the bicycle industry). Time fixed effects, λ_t, absorb aggregate shocks (e.g., business cycle fluctuations, China joining the WTO, etc.). The vector $\mathbf{X}_{i,j,t}$ controls for unobserved firm-level heterogeneity to ensure that estimates are not biased by omitted determinants of investment in innovation.[17] First, we control for the firm size using the log number of workers as suggested in the literature. This is important since firm size could be a determinant of its propensity to invest in innovation. Second, we control for the ownership structure of firms that can be important to determine firms' financial structure

[15] Alternatively, Feenstra et al. (2014) suggest to exclude firms for which some key accounting identities are not matched in the data. This results in a quite rigorous filtering, however, which would substantially shrink our sample of durable good firms.

[16] Depending on the length of the time window, we have to exclude certain industries from the analysis, e.g. since satellite dish ownership is only available from 2006 onwards, we have to exclude this industry in our baseline analysis with the five-year time window.

[17] See Crépon et al. (1998) and Mairesse and Mohnen (2010) for a review of firm-level innovation determinants.

and innovativeness.[18] Specifically, we take privately owned firms as the reference group and introduce three dummy variables for whether a firm is foreign, state or collective owned. Third, we add a dummy for firms that are older than six years (the median in our sample) in order to control for the age of firms.[19] Further, we include a dummy for firms located in coastal provinces, worrying that firms in the booming coastal regions might be overrepresented in some sectors. Finally, to control for different intensities of market competition across sectors, we introduce the Hirschmann-Herfindahl index, which is defined as the sum of squared market shares of all firms within the sector.[20] Summary statistics on all variables are listed in table A.4.

The coefficient of interest, α, captures the effect of future market size on a firm's investment in technology. The theory of directed technical change outlined in the introduction predicts that α should be positive. As both our dependent variable and market size are in logs, the coefficient can be interpreted as an elasticity. We now discuss how we address a number of econometric concerns.

4.3.2 Endogeneity and Potential Market Size

The most important econometric issue is the potential endogeneity of the market size measure. Firms' investments in technology adoption can influence the future stream of durable good purchases by affecting the prices or the quality of durable goods. For instance, process innovation reduces production costs, whereas product innovation makes available better varieties for which consumers are willing to pay more. Through these channels, a higher intensity of innovation in an industry may increase the industry's future market size. Due to the endogeneity problem, OLS regressions may yield inconsistent estimates of the parameter α. To address this problem, we instrument $MS^{actual}_{j,t,t+4}$ with a measure of potential market size, $MS^{potential}_{j,t,t+4}$ which is independent of supply shocks affecting the prices or the quality of durable goods. The identification strategy is in close spirit to the one employed by Acemoglu and Linn (2004). They use demographic variables to predict the evolution of market size for different drugs, taking into account the usage pattern across age groups in the population. Intuitively, a fast-aging population implies that the market for drugs used to treat patients suffering from the Alzheimer syndrome grows

[18] See for example Song et al. (2011).

[19] Arnold and Hussinger (2005) for example argue that due to possible correlation between size and age of a firm employing a dummy instead of the absolute age seems to be the correct estimation approach.

[20] Studies that specifically employ the HHI are for example Cotterill (1986), Farrell and Shapiro (1990a) and Farrell and Shapiro (1990b). We define the HHI for industry j at time t as the sum of squared market shares (in value added) of all firms operating within this sector at time t. Since we calculate market shares in percentage terms, (between 0 and 100), the HHI lies in the range between 0 and 10 000. We are aware of the fact that the border of markets is less clear for globally operating firms. However, we consider the HHI as the first best measure to capture market competition within the firm's primary (home) market.

faster than that for drugs used to treat child obesity. Their demography-based measure of potential market size is exogenous to innovative investments, and is therefore a valid instrument. Similarly, in our paper we assume that the market size of each durable good depends on the evolution of income growth and the income distribution, given the diffusion curve associated with each durable good. In particular, we assume that households in different income brackets purchase each durable good with a given probability that we estimate. Then, we construct a measure of *potential* market size for each durable good that depends only on macroeconomic variables (e.g. the growth of household income) and not on supply-driven shocks. Under the assumption that macroeconomic changes are exogenous to firms (and industries) investing in new technologies, market potential is a valid instrument for the actual market size. Note that the exclusion restriction would be violated if the innovative investments of firms producing a particular good could affect the future aggregate economic growth (or income distribution) in China. However, this is unlikely to be the case since we focus on narrowly defined industries producing small shares of the total income of China.[21]

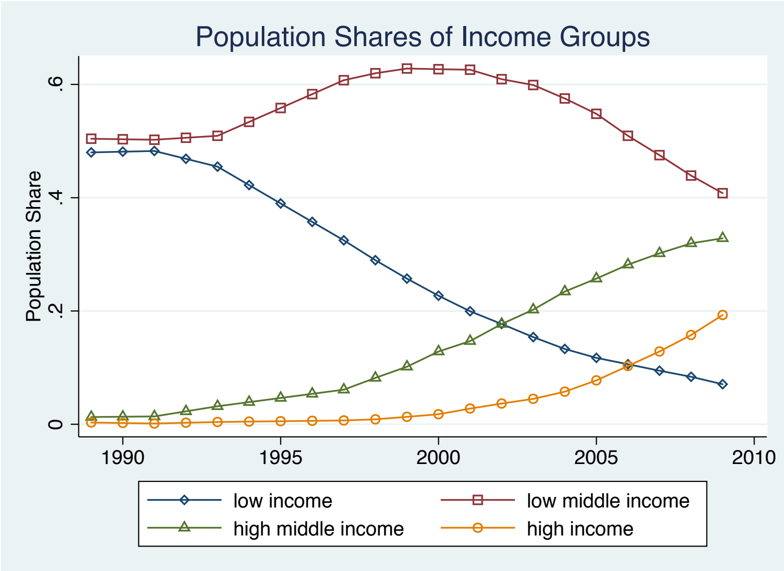
More formally, we start from breaking down the Chinese population into four groups using fixed income thresholds in constant 2009 Yuan.[22] Figure 4.3 shows the evolution of the population shares of the four income groups over the survey period. The population share of the two poorer groups falls dramatically over time, especially between 2000 (85 %) and 2009 (47%). Conversely, the share of high income households increases from almost zero in 1997 to 20% in 2009. Together, the two upper income groups account to 52% in 2009.

Next, we construct the usage intensities, $u_{j,g,t}$, by estimating the number of items per capita of each durable good j owned by agents in income group g at time t. Table A.2 in appendix presents these usage profiles for the year 2009 in our dataset. As expected, the usage profiles are upward sloping for all durable goods. Yet, there are considerable differences between durable goods. Electric fans, for instance, feature the largest increase in usage at the lower end of the income distribution whereas the usage of cars increases the most as an individual switches from the second highest to the highest group. These differences across usage patterns are the crux of our identification.

[21] Also, although investments in innovation are correlated across industries, recall that we control for time dummies in our regressions, so the identification comes from deviations from common trends in TFP.

[22] Households are assigned to four income groups according to their household income per capita following a classification of the World Bank (2009) Atlas method that assigns countries into 4 groups according to their GNI per capita in 2009. With some adjustments to account for small sampling of the high income group, the groups are: low income (below 2'150 Yuan), lower middle income (2'150 - 8'514 Yuan), upper middle income (8'515 - 16'499 Yuan), high income (16'500 Yuan or more). In constant 2009 US $, this corresponds roughly to: low income, US $ 2'149, low middle income, US $ 2'150 -US $ 4'167, high middle income, US $ 4'168 - US $ 8'075, high income, US $ 8'076 or more. See data appendix 4.B.1 for details.

Figure 4.3: Evolution of Income Groups According to WB Classification



Notes: CHNS data 1989 to 2009. Households classified into four income groups according to their household income per capita in constant 2009 Yuan: low income (below 2'150 Yuan), lower middle income (2'150 - 8'514 Yuan), upper middle income (8'515 - 16'499 Yuan), high income (16'500 Yuan or more).

Finally, we construct our measure of potential market size as

$$MS_{j,t,t+1}^{potential} = \left(Stock_{j,t+1}^{potential} - Stock_{j,t}^{potential}\right) + \delta_j \cdot Stock_{j,t}^{potential},$$

where

$$Stock_{j,t}^{potential} = \sum_g \overline{u}_{j,g} \cdot i_{g,t},$$

and $i_{g,t}$ is the number of people in income group g in year t and $\overline{u}_{j,g} = u_{j,g,t=2009}$ is the number of item of durable good j owned per head in income group g in the year 2009.[23] Our measure exploits the fact that there are significant differences in the ownership of durable goods across income groups. As the economy grows, more households enter higher income groups and start purchasing durable goods. This process affects asymmetrically the demand of different durable goods. As table A.2 shows, durable goods whose diffusion increases the most across low income groups (such as electric fans or motorcycles), diffuse faster at an earlier stage of development. In contrast, for goods such as cars, the diffusion

[23]Note that the choice among different CHNS waves as base-year is to some extent arbitrary. Because the 2009 wave of the CHNS has the richest coverage of durable goods and the highest income group is sampled more accurately than in earlier years, we pick 2009 as our best choice of a base-year. See appendix 4.B.1 for a detailed discussion.

is fastest as more households climb up into the highest income group. Note that there are differences between $MS^{potential}_{j,t,t+1}$ and $MS^{actual}_{j,t,t+1}$. Part of these differences reflect changes (typically, increases) in the usage intensities that apply to all income groups. Beerli (2010), shows that a large part of these is explained by falls in prices.[24] Price-driven changes in demand, in turn, are likely to be related to supply-side shocks, e.g. technical progress reducing the production cost. Our measure of potential market size abstracts from such changes and is therefore immune from supply-side shocks. In other words, changes in prices and quality of durable goods which may result from investments in technology adoption, cannot cause over-time variation in $MS^{potential}_{j,t,t+1}$.[25] In fact, figure A.1 in the appendix reveals that income-specific usage rates are indeed changing due to differential price dynamics. Moreover, the variation across industries shows the differential speed of technological progress across industries.

4.3.3 Omitted Variables

The estimate could also suffer from an omitted variable bias. In this respect, we address two important specific issues. First, while we focus on the expansion of the domestic durable good market, Chinese firms also engage in a significant export activity. Thus, investment in new technologies may be driven by foreign demand as well. We address this issue in two ways: first, we include a dummy capturing whether a firm is engaged in export activities. Second, to analyze whether exporting firms are significantly different from domestic-serving firms, we additionally include an interaction term between our market size measure and the export indicator.
Another potential source of bias could be global technology shocks which affect differentially the propensity of firms to innovate in different industries. An example could be the rise of automation technology (compare e.g. Autor et al. (2003). To address this concern, we control for an industry-specific measure of worldwide technology potential reported by Swiss firms.

[24] An example is color TVs. Beerli (2010) shows that the rise in income levels can only explain about one third of the total increase in color TV ownership for an average household between 1989 and 2006.

[25] We are particularly concerned that innovation activities of firms in year t may affect future usage intensities, i.e. $u_{j,g,t+k}$ with $k > 0$, and through this the expected market size in upcoming years, $MS^{actual}_{j,t,t+k}$. Thus, a less conservative notion of potential market size would allow to use lagged usage intensities for each given year. Yet, as innovation activities of firms show considerable serial correlation, we take the most conservative approach possible and fix usage intensities to one specific year.

4.4 Results

4.4.1 OLS and IV Regressions

We start by estimating a set of standard OLS regressions, whose results are reported in table 4.1. All regressions include time and industry fixed effects. Standard errors are clustered at the industry-year level. Namely, we allow for correlation between error terms related to observations belonging to the same industry in each given year.[26]

Table 4.1 reports the results. We do not report the estimated coefficients for the full set of control variables, which are deferred to the appendix (see appendix table A.8). Column 1 yields the estimate of α in the baseline OLS regression without controls. The coefficient is positive and highly significant. Increasing the future market size by one percent raises firms' TFP by 0.19%. However, part of the effect could be spuriously driven by omitted time-varying firm characteristics. We then control for a large number of firm-level variables including size, ownership, age, and location.[27] We also control for the Hirschmann-Herfindahl index for market competition at the industry level. Controlling for these firm and industry characteristics causes a reduction in the size of the estimated coefficient, which falls to 0.6% turning statistically insignificant, see column 2 of table 4.1. Clustering at the firm-level reduces the estimated standard error but the coefficient of interest remains insignificant (see column 3).

Next, we run two-stage least squares (2SLS) regressions to account for the endogeneity of the actual market size measure. We use our measure of "potential market size" as an instrument for the actual market size. As explained in section 4.3.2, potential market size is exclusively driven by future changes in the income distribution. This measure is orthogonal to price or quality changes that could affect changes in ownership patterns and cause an endogeneity problem. Formally, for this to be a valid instrument, it must be correlated with the actual market size and be uncorrelated with the error term.

The results of the 2SLS regressions are reported in columns 4 to 6 of table 4.1. The effect of market size on firms' TFP is larger and more precisely estimated than in the OLS specification. Column 4 repeats the regression of column 1, where we control only for

[26]We also consider an alternative clustering strategy allowing for correlation of the error terms at the firm-level. Clustering at the industry-year level turns out to be generally more demanding. An even more demanding strategy would be to cluster standard errors at the industry level. However, this is not possible with our data, since the number of clusters would in this case be too small (see Angrist and Pischke (2009) for a discussion of the problems arising with too few clusters). Following Angrist and Pischke (2009), we check the validity of our results by collapsing observations on the industry level.

[27]See Crépon et al. (1998) and Mairesse and Mohnen (2010) for a review of firm-level innovation determinants.

industry and time fixed effects. The estimated coefficient is positive and highly significant. Controlling for the firm- and industry level characteristics listed above yields a lower coefficient. However, this remains large and highly significant. The estimate in column 5 - the analogue of the OLS regression in column 2 - implies that a one percent exogenous increase in market size leads to an increase in TFP of 0.27%. This is a large effect (more than four times as large as the OLS estimate), suggesting the importance of profit incentives as a driver of firms' innovation activities. Column 6 completes the picture by clustering the standard errors at the firm-level. This yields an even higher p-value of the estimated coefficient.[28]

Table 4.1: Effect of Market Size on Log TFP

Dep. Variable	$\ln TFP_{i,j,t}$					
Mean	5.137	5.137	5.137	5.137	5.137	5.137
St.Dev.	1.161	1.161	1.161	1.161	1.161	1.161
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln MS^{actual}_{j,t,t+4}$	0.188	0.0628	0.0628	0.549	0.272	0.272
	[0.0813]**	[0.0525]	[0.0395]	[0.185]***	[0.132]**	[0.0828]***
Firm Controls	No	Yes	Yes	No	Yes	Yes
Method	OLS	OLS	OLS	2SLS	2SLS	2SLS
Observations	20,167	20,160	20,160	20,167	20,160	20,160
R^2	0.111	0.278	0.278	0.106	0.277	0.277
Clustering	Ind. x Year	Ind. x Year	Firm	Ind. x Year	Ind. x Year	Firm
No of Clusters	111	111	7662	111	111	7662
F-Stats				27.68	26.70	1480

Notes: ***, **, * denote significance on the 1%, 5% and 10% level, respectively. Observations below the 10 percentile of value added each year are excluded. All columns include year and industry fixed effects. Columns (2)-(3) and (5)-(6) include a set of firm- and industry-level controls (the log of number of workers, age (measured by a dummy), a dummy for collective, state and foreign ownership, coastal location, respectively and the Hirschmann-Herfindahl index). $\ln MS^{actual}_{j,t,t+4}$ is instrumented with $\ln MS^{potential}_{j,t,t+4}$.

Table 4.2 presents the results of the first stage regressions. Columns 1 and 2 show the results corresponding to columns 4 and 5 in table 4.1. Potential market size is significantly correlated with the actual measure of market size and suggests that a one percent change in potential market size (driven only by income changes) leads to a change in actual market size by nearly 2%. The last row of table 4.2 shows that the F-statistic of the excluded instrument is well above the conventional threshold of 10.[29] Column 3 repeats

[28]The standard error of the estimated coefficient blows up if we cluster residuals at the industry level, rendering the estimated coefficient insignificant. However, as discussed above, this approach is problematic, and we do not emphasize it.

[29]Compare e.g. Staiger and Stock (1997) for details on the critical F-statistic that reveals a weak instrument problem.

the regression of column 2 clustering standard errors at the firm-level.

Table 4.2: First Stage Regression

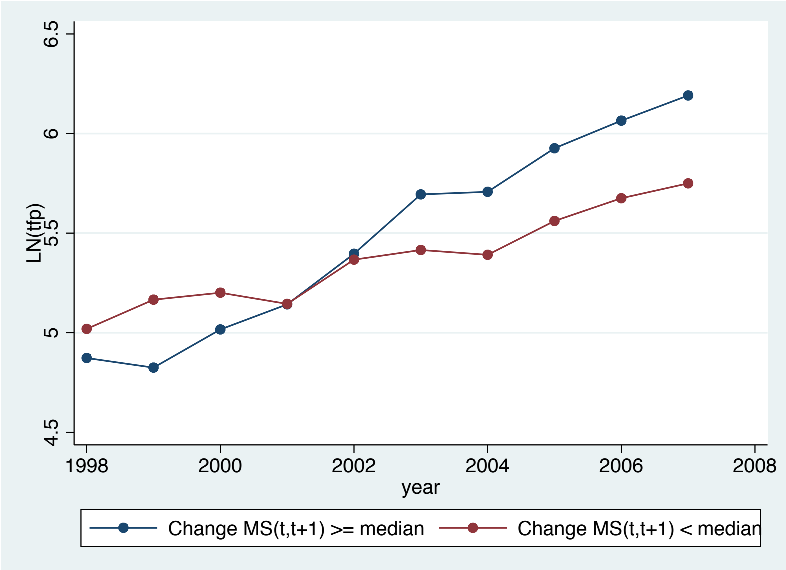
Dep. Variable	$\ln MS^{actual}_{j,t,t+4}$		
	(1)	(2)	(3)
$\ln MS^{potential}_{j,t,t+4}$	1.967	1.955	1.955
	[0.374]***	[0.378]***	[0.0508]***
Firm controls	No	Yes	Yes
Observations	20,167	20,160	20,160
R^2	0.244	0.239	0.239
Clustering	Ind. x Year	Ind. x Year	Firm
No of Clusters	111	111	7662
F-Stats	27.68	26.70	1480

Notes: ***, **, * denote significance on the 1%, 5% and 10% level, respectively. Observations below the 10 percentile of value added each year are excluded. All columns include year and industry fixed effects. Columns (2)-(3) include a set of firm- and industry-level controls (the log of number of workers, age (measured by a dummy), a dummy for collective, state and foreign ownership, coastal location, respectively and the Hirschmann-Herfindahl index). The reported R^2 reported equals the partial R^2.

Finally, figure 4.4 summarizes our empirical findings by a convenient visualization. We split our data sample at the median value of the change in potential market size between 1998 and 2007.[30] Then we plot the evolution of log productivity broken down by above - and below median industries. Since we empirically stress the importance of the market size effect for firms' innovation behavior, we expect TFP to increase faster for firms within industries that are subject to a positive demand shock over the sample period. The figure shows that this is indeed the case. Productivity increased by 1.3 log points in industries above the median change in market size between 1998 and 2007 whereas industries below increased by 0.7 log points.

[30]We calculate the median value of the change in one-year potential market size between 1998 and 2007. For each industry, this value is $\Delta MS^{potential}_{j,1998,2007} = \ln MS^{potential}_{j,2007,2008} - \ln MS^{potential}_{j,1998,1999}$. Looking at the change in potential market size ensures that we ignore level differences of market size between industries, as we do later in the regression when we use industry fixed effects.

Figure 4.4: Evolution of Log Productivity in Industries Above and Below the Median Change in Potential Market Size Between 1998 and 2007



Notes: All ASIP data 1998 to 2007. Industries allocated to groups according to the change in market size between 1998 and 2007, i.e. $\Delta MS^{potential}_{j,1998,2007} = \ln MS^{potential}_{j,2007,2008} - \ln MS^{potential}_{j,1998,1999}$. Industries above the median, $\Delta MS^{potential}_{j,1998,2007} >= \Delta \overline{MS}^{potential}_{1998,2007}$, are camera, air condition, computer, car, radio, refrigerator, telephone and kitchen appliances. Industries below the median, $\Delta MS^{potential}_{j,1998,2007} < \Delta \overline{MS}^{potential}_{1998,2007}$, are washing machine, sewing machine, home video appliances, cycles, electric fan, motorcycle, satellite dish. The mean value of $\ln TFP_{j,t}$ within groups was calculated using each industry's value added as weight. The cellphone industry is omitted from this figure as it is only covered in the ASIP after 2003.

4.5 Robustness

4.5.1 Trimming

In the regressions of table 4.1, we use a trimmed sample excluding the smallest 10% of the firms in terms of value added on a yearly basis. The exclusion of small firms is motivated by the fact that the TFP estimates of small firms are very noisy. In this section we show the sensitivity of the results with respect to alternative trimming thresholds. Column 3 of table 4.3 shows the baseline 2SLS estimation (column 5 in table 4.1), for reference, while columns 1 and 2 and 4 and 5 show the results of the corresponding regressions under different thresholds.[31] The coefficient of interest becomes larger and more precisely estimated the more we trim. No trimming at all yields a coefficient of 0.17, statistically insignificant (see column 1 of table 4.3). Trimming 5% of the observations yields a coefficient of 0.23 (compared with 0.27 in the benchmark case) which is significant at the 10 percent level. Restricting the dataset further by trimming 25% and 50% respectively, yields even larger coefficients. Note also that the standard error of TFP decreases the more we trim the sample, suggesting that measurement error may be more severe among small firms.

Table 4.3: Robustness Analysis: Trimming

Dep. Variable	$\ln TFP_{i,j,t}$				
Mean	4.894	5.044	5.137	5.370	5.783
St.Dev.	1.395	1.215	1.161	1.085	1.007
	(1)	(2)	(3)	(4)	(5)
$\ln MS^{actual}_{j,t,t+4}$	0.167	0.231	0.272	0.382	0.485
	[0.131]	[0.136]*	[0.132]**	[0.136]***	[0.137]***
Method	2SLS	2SLS	2SLS	2SLS	2SLS
Observations	22,328	21,241	20,160	16,900	11,412
R^2	0.303	0.287	0.277	0.249	0.212
Trimming	0%	5%	10%	25%	50%
F-Stats	27.32	26.95	26.70	27.27	28.41

Notes: ***, **, * denote significance on the 1%, 5% and 10% level, respectively. Robust standard errors (clustered on the industry-year level jt) are given in parentheses. All columns include year and industry fixed effects as well as a set of firm- and industry-level controls (the log of number of workers, age (measured by a dummy), a dummy for collective, state and foreign ownership, coastal location, respectively and the Hirschmann-Herfindahl index). $\ln MS^{actual}_{j,t,t+4}$ is instrumented with $\ln MS^{potential}_{j,t,t+4}$.

[31]The corresponding first stage regressions are found in appendix table A.11.

4.5.2 Omitted Variables

A natural concern with our investigation is China's export market. One might suspect the export market to be a key driver of investments in an export-oriented economy like China. As table A.4 and figure A.2 show, 49% of all firms in the durable good industries considered in our study engage in export activities. The export exposure varies considerably across industries. For instance, the average fraction of sales going to foreign markets is high for camera and radio manufacturers (60% and 58%, respectively), while it is fairly low for car and refrigerator manufacturers (2% and 13%, respectively).[32] In table 4.4 we show that our previous results are robust to controlling for export behavior.[33] Column 1 is the same as column 5 in table 4.1. In column 2, we include among the regressors an indicator for whether a firm has positive export sales. As expected, we find that exporters are on average more productive than non-exporters; yet, the inclusion of this dummy leaves the coefficient of interested practically unchanged. In column 3, we add an interaction term between the exporter dummy and the market size measure to investigate whether the effect of the domestic market is systematically different between exporters and non-exporters. The coefficient of the interaction term shows that the effect of the domestic market on innovation is stronger for non-exporters than for exporters. The difference is statistically significant. Alternatively, we estimate the market size effect separately for exporters and non-exporting firms. Again, we find the coefficient of market size to be highly significant (and substantially larger) for non-exporting firms only, while exporting firms show no effect (see appendix table A.9). Both results are consistent with the view that the expansion of the domestic market size is less important for globally active firms.[34]

Another concern is that global technology shocks could affect the innovation behavior of firms and be correlated with the dynamic of the domestic market.[35] To control for global technology shocks, we include a survey measure of technological opportunities constructed according to the assessment of Swiss firms as reported by the KOF Innovation Survey (2012). In this survey, firms are asked to assess the worldwide availability of technological know-how in private and public hands which could be used to generate marketable new products.[36] Swiss firms have traditionally occupied a strong position in international

[32]Detailed descriptive statistics on the industry level are found in Tables A.5 - A.7 in appendix 4.A.2.

[33]The corresponding first stage regressions are found in appendix 4.A.2.

[34]In fact, figure A.2 shows that the distribution of firms ranked by their export share relative to total sales is highly bimodal. Thus, firms seem to serve either only the domestic or exclusively the foreign market, which explains the insignificance of the market size effect for exporters.

[35]In a recent survey of the literature, Draca et al. (2006) show that there was a considerable impact of ICT availability on productivity. Additionally, Bloom et al. (2012) show the effect of IT on productivity was differential even within industries depending on whether firms were US- or non-US-multinationals.

[36]The KOF Innovation Survey (KOF, 2012) covers a representative sample of Swiss firms in the manufacturing, construction and service sector on a three yearly basis since 1990. To the best of our knowledge,

science and technology activities (see OECD (2013), Arvanitis et al. (2010)). Thus, the information reported by Swiss firms reflect to a considerable degree these global trends in technology. We match this technology potential measure to our durable good industries on a fine grained three or two digit industry level. This variable shows considerable variation across time and over industries (see figure A.3).[37] As can be seen in column 4, controlling for global technology shocks does not affect significantly the market size effect on TFP. Controlling for both technology shocks and exports (column 5) has no significant effect on the coefficient of market size either.

Table 4.4: Robustness Analysis: Controlling for Exports and Technology Supply Shocks

Dep. Variable	$\ln TFP_{i,j,t}$				
Mean	5.137	5.138	5.138	5.137	5.138
St. Dev.	1.161	1.160	1.160	1.161	1.160
	(1)	(2)	(3)	(4)	(5)
$\ln MS^{actual}_{j,t,t+4}$	0.272	0.274	0.288	0.265	0.267
	[0.132]**	[0.133]**	[0.124]**	[0.135]**	[0.136]**
$\ln MS^{actual}_{j,t,t+4} \times 1(EXP_{i,j,t} > 0)$			-0.152		
			[0.0286]***		
$1(EXP_{i,j,t} > 0)$		0.0539	2.635		0.0540
		[0.0274]**	[0.486]***		[0.0274]**
$TECHPOT_{j,t}$				-0.00541	-0.00558
				[0.0236]	[0.0240]
Method	2SLS	2SLS	2SLS	2SLS	2SLS
Observations	20,160	20,147	20,147	20,160	20,147
R^2	0.277	0.277	0.280	0.277	0.277
F-Stats	26.70	26.88		21.17	21.31
F-Stats1			40.31		
F-Stats2			839.5		

Notes: ***, **, * denote significance on the 1%, 5% and 10% level, respectively. Robust standard errors (clustered on the industry-year level jt) are given in parentheses. Observations below the 10 percentile of value added each year are excluded. All columns include year and industry fixed effects as well as a set of firm- and industry-level controls (the log of number of workers, age (measured by a dummy), a dummy for collective, state and foreign ownership, coastal location, respectively and the Hirschmann-Herfindahl index). $1(EXP_{i,j,t} > 0)$ is one if a firm has positive export sales. $\ln MS^{actual}_{j,t,t+4}$ is instrumented with $\ln MS^{potential}_{j,t,t+4}$ and $\ln MS^{actual}_{j,t,t+4} \times 1(EXP_{i,j,t} > 0)$ with $\ln MS^{potential}_{j,t,t+4} \times 1(EXP_{i,j,t} > 0)$. $TECHPOT_{j,t}$ is the world wide technology potential assessed by Swiss firms in the KOF Innovation Survey.

the KOF Innovation Survey is the only publicly available innovation survey which can be used on a highly disaggregate sector level (four digits). Additionally, we check for robustness of this measure using standard innovation measures such as R&D spending, the number of patents and new product outputs share on the same industry level.

[37]To maximize accuracy and cross-industry variation, we use three digit industry levels whenever the data allows us to do so. If an industry is not available in the Swiss firm sample we take the next higher industry classification. This allows us to get variation over eight different durable good industries.

4.5.3 Using Labor Productivity instead of TFP

In this section, we consider (the log of) labor productivity as an alternative dependent variable. While labor productivity may increase due to capital deepening, rather than investment in innovation, it has the advantage of being a less noisy measure than TFP. Labor productivity is computed as the value added per employee. Table 4.5 displays the results.[38] All regressions include the full set of control variables used in table 4.1. Column 1 shows the result of the OLS regression - the coefficient of market size is now positive and highly significant, contrary to table 4.1. Column 2 shows our preferred specification. The effect is again positive and significant. An increase in market size by one percent yields an increase of 0.4% in firm's labor productivity. Again, the 2SLS estimates are larger than the corresponding OLS estimate. Column 3 shows the results when standard errors are clustered at the firm-level. Finally, column 4 of table 4.5 shows that results are robust to the inclusion of the additional controls for export behavior of firms and the technology potential measure to account for supply-side drivers (as discussed in section 4.5.2).

Table 4.5: IV Regression on Log Laborproductivity

Dep. Variable	$\ln Laborproductivity_{i,j,t}$			
Mean	3.932	3.932	3.932	3.933
St.Dev.	1.148	1.148	1.148	1.148
	(1)	(2)	(3)	(4)
$\ln MS^{actual}_{j,t,t+4}$	0.178	0.401	0.401	0.424
	[0.0696]**	[0.160]**	[0.0858]***	[0.171]**
$1(EXP_{i,j,t} > 0)$	No	No	No	Yes
$TECHPOT_{j,t}$	No	No	No	Yes
Method	OLS	2SLS	2SLS	2SLS
Observations	20,160	20,160	20,160	20,147
R^2	0.178	0.176	0.176	0.177
Clustering	Ind. x Year	Ind. x Year	Firm	Ind. x Year
No of Clusters	111	111	7662	111
F-Stats		26.70	1480	21.31

Notes: ***, **, * denote significance on the 1%, 5% and 10% level, respectively. Observations below the 10 percentile of value added each year are excluded. All columns include year and industry fixed effects and a set of firm- and industry-level controls (the log of number of workers, age (measured by a dummy), a dummy for collective, state and foreign ownership, coastal location, respectively and the Hirschmann-Herfindahl index). Column (4) in addition introduces a dummy for positive exports, $1(EXP_{i,j,t} > 0)$ and the supply side control, $TECHPOT_{j,t}$. $\ln MS^{actual}_{j,t,t+4}$ is instrumented with $\ln MS^{potential}_{j,t,t+4}$.

[38] The corresponding first stage regressions are found in appendix table A.14.

4.5.4 Regressions on the Industry Level

Since our innovation measure comes from the firm-level data set but the market size effect is identified at the industry level, there may be a risk of underestimating the standard errors. Although we cluster standard errors at the industry-time level, a remaining concern is that observations may be correlated at the industry level over different periods. While clustering at the industry level would resolve this issue, this avenue is not possible due to an insufficient number of clusters. As a way to mitigate concerns, we check if the results are robust to collapsing all firm-level observations at the industry level and re-run our baseline regressions using a weighted least squares approach, using the number of firms within each industry as weights, as suggested by Angrist and Pischke (2009). In addition, we control for heteroscedasticity among error terms and report robust standard errors. Table 4.6 displays similar regressions shown in table 4.1 using either TFP (columns 1 to 3) or labor productivity (columns 4 to 6) as the dependent variable.[39] All specifications include the full set of industry and time fixed effects and the set of control variables of size, age, region, market competition, ownership structures. Columns 3 and 6 additionally control for export behavior and technology potential as supply side driver (see above). In particular, the new set of controls is defined as the (unweighted) mean over all firm-level variables within one industry and each year including the mean of dummies such as ownership.[40]

The results are similar to those in table 4.1. In our preferred 2SLS specification with the full set of controls (see columns 3 and 6 of table 4.6), an increase of industry's market size by one percent translates into an increase in TFP of about 0.68% and into an increase in labor productivity of about 0.7%.[41] These results are reassuring and provide additional credibility to the firm-level analysis.

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[39] In particular, we focus on the specifications that include the full set of firm-level controls.

[40] Corresponding first stage regressions are found in table A.15 in appendix.

[41] Note that the F-statistics in columns 2 and 5 are below the conventional level of 10. Thus, these regressions are subject to a mild weak instrument problem and we prefer the specification with all control variables including export behavior and technology potential.

Table 4.6: Effect of Market Size on Log TFP

Dep. Variable	$\ln TFP_{i,j,t}$			$\ln Laborproductivity_{i,j,t}$		
Mean	5.772	5.772	5.772	4.544	4.544	4.544
St.Dev.	0.597	0.597	0.597	0.641	0.641	0.641
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln MS^{actual}_{j,t,t+4}$	0.184	0.643	0.678	0.400	0.579	0.709
	[0.0720]**	[0.238]***	[0.205]***	[0.0914]***	[0.255]**	[0.200]***
Method	OLS	2SLS	2SLS	OLS	2SLS	2SLS
Observations	111	111	111	111	111	111
R^2	0.961	0.942	0.939	0.959	0.956	0.952
F-Stats		7.459	15.25		7.459	15.25

Notes: ***, **, * denote significance on the 1%, 5% and 10% level, respectively. Robust standard errors are given in parentheses. Observations below the 10 percentile of value added each year are excluded. All columns include year and industry fixed effects as well as the simple industry mean of the set of firm- and industry-level controls (the log of number of workers, age (measured by a dummy), a dummy for collective, state and foreign ownership, coastal location, respectively and the Hirschmann-Herfindahl index). Column (3), (6) in addition introduce a dummy for positive exports, $1(EXP_{i,j,t} > 0)$ and the supply side control, $TECHPOT_{j,t}$. $\ln MS^{actual}_{j,t,t+4}$ is instrumented with $\ln MS^{potential}_{j,t,t+4}$. Regressions are weighted by the number of firms within a sector.

4.6 Conclusion

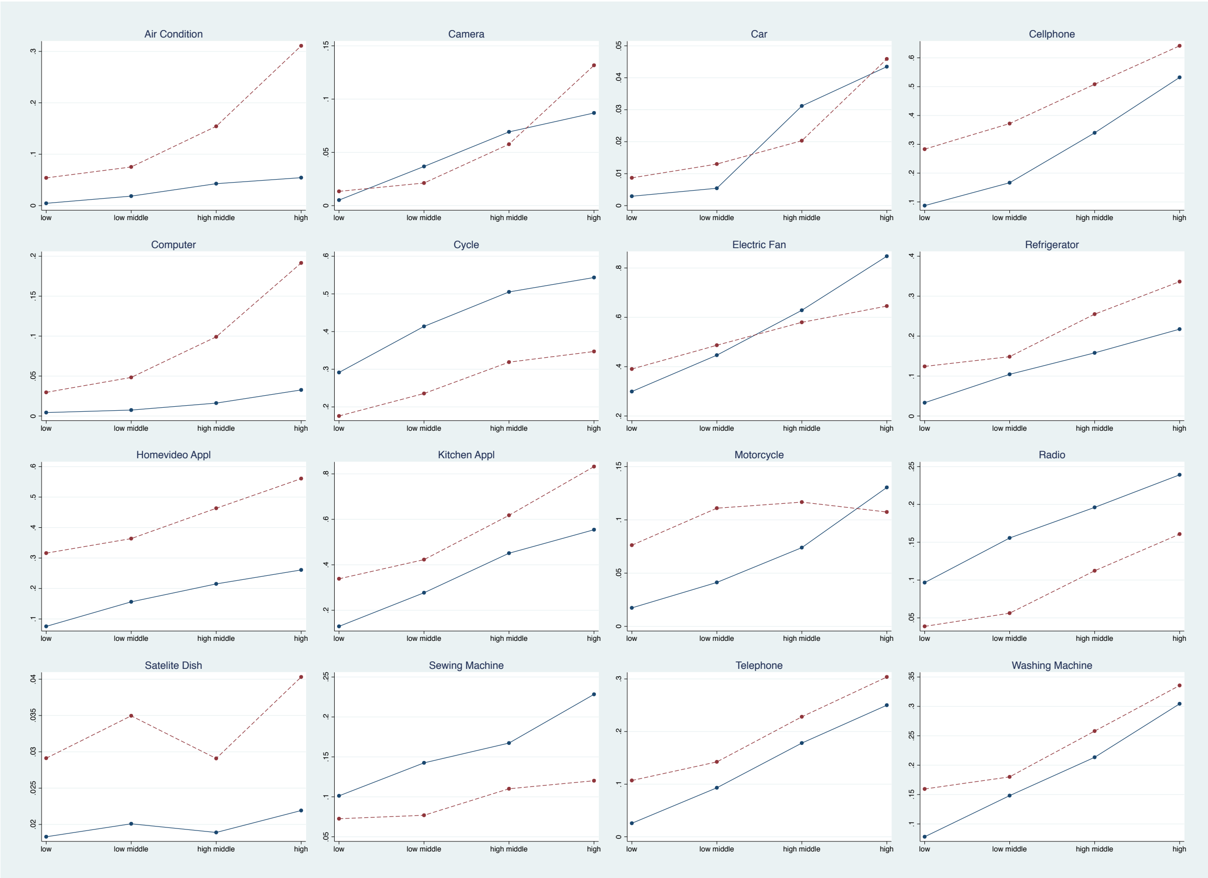
Much of the previous literature studying determinants of the spectacular growth performance of the Chinese economy has focused on supply- and technology-factors, while the role of demand forces is still poorly understood. This paper focuses on firm's expectations about future market size as a potentially important channel that contributes to our understanding of technical progress in the Chinese manufacturing sector. The basic source of variation for potential market size comes from Chinese growth and its huge (and predictable) impact on the Chinese income distribution. In 1990, 99 percent of Chinese consumers had an income lower than 8500 Yuan (at constant 2009 prices) and were low- or lower-middle income households according to World Bank Classification. By the year 2009, this fraction had fallen to 50 percent. The associated change in the Chinese income distribution did not affect industries equally. To the extent that the Engel-curves for the industry's various products is non-linear, industries are affected differentially. It is this source of variation that underlies our identification strategy.

To establish an empirical link between expected market size and technical progress, we combine household-expenditure data from Chinese Health and Nutrition Survey (CHNS) and firm-level data from the Annual Survey of Industrial Production (ASIP). Looking at 16 industries covering a substantial share of household expenditures for consumer durables, CHNS data allows us to construct product-specific Engel-curves for the 16 consumer durables. Combining these income-driven changes in consumer behavior with information on the income distribution (income-class specific population shares) allows us to estimate a measure of expected market size, whose evolution over time is entirely driven by income growth. Using firm-specific productivity data estimated from ASIP data, we ask how firm performance is affected by expected market size. Our findings suggest that demand effects are quantitatively important: a one percent increase in expected market size increases firm-specific TFP by 0.27% and firm-specific labor productivity by 0.42%. Firms in industries with a large expected local market are significantly more productive today, and show higher levels of other measures of innovative activity. We think that, in the future, the role of demand forces may become even stronger as a driver of Chinese growth than they were in in the recent past. China's share of private consumption in total GDP is still quite low by international standards and may converge to international levels in the future. Together with sustained economic growth, the size of the Chinese home market will become as important as the export market making Chinese firms less dependent on exports and let them focus more closely on the home market. Our results suggest that these dynamics from the demand side may have important implications for technical progress and may help to sustain high Chinese growth also in the years to come.

4.A Appendix

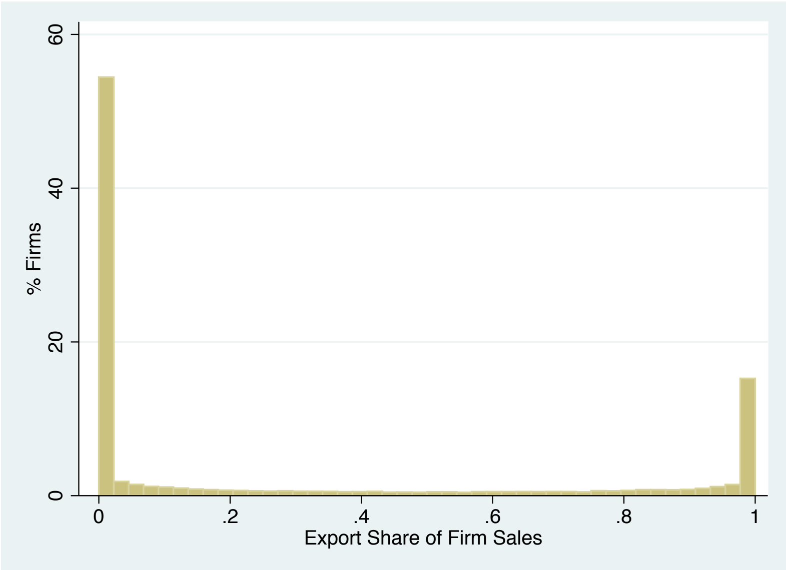
4.A.1 Figures

Figure A.1: Dynamic in Usage Intensities for Given Income Groups



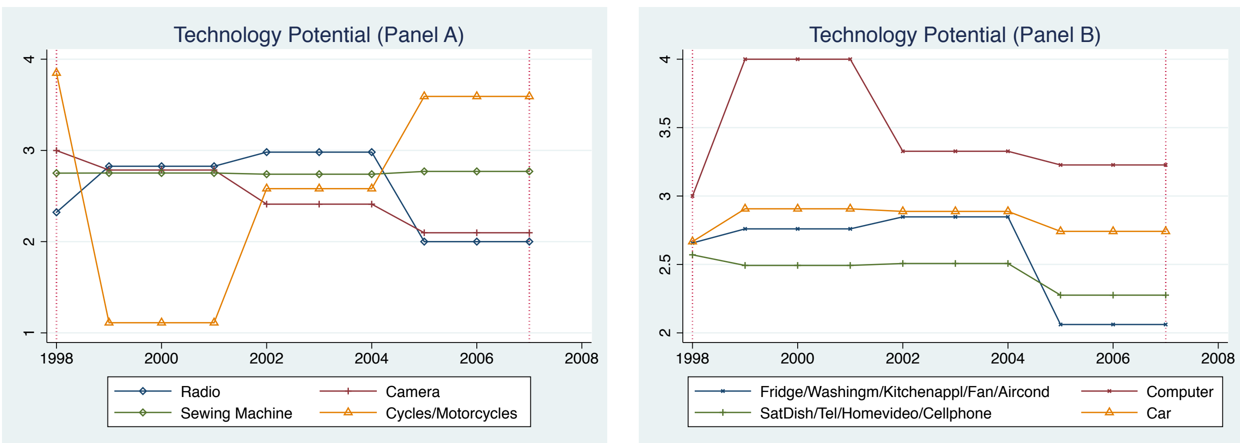
Notes: CHNS data. Usage per head on the y-axis (different scales), the four income groups on the x-axis in ascending order. The solid line represents the usage profile, $u_{j,g,t}$, in the first survey period available before our analysis period. For most goods this is 1997 whereas it is 2004 for cellphones and 2006 for satellite dishes. The dashed line represents the usage profile for the latest wave available in the CHNS. For most goods this is 2009 whereas it is 2006 for radios. Income groups are defined as described in Section 4.3.2.

Figure A.2: Share of Firms Engaging in Exports



Notes: The figure plots the number of firms (in percentage terms) as a function of the export share relative to total firm sales. Data is based on the 10% trimmed sample (see Section 4.2.2). Source: ASIP dataset.

Figure A.3: Dynamic of Technology Potential



Notes: KOF Innovation Survey matched to ASIP data.

4.A.2 Tables

Table A.1: Table: Service Life and Depreciation Rates of Durable Goods

Durable Good	Service Life L_j	Category in BEA (2003)
air condition	11	other household appliances
camera	10	photographic equipment
car	8	other motor vehicles
cellphone	9	computer and peripheral equipment
computer	9	computer and peripheral equipment
cycles	10	wheel goods
electric fan	10	other durable house furnishings
refrigerator	11	kitchen and other household appliances
homevideo appliances	9	video and audio products
kitchen appliances	11	kitchen and other household appliances
motorcycle	8	other motor vehicles
radio	9	video and audio products
satellite dish	10	other durable house furnishings
sewing machine	10	other durable house furnishings
telephone	10	other durable house furnishings
washing machine	11	kitchen and other household appliances

Notes: Source: BEA (2003).

Table A.2: Usage Profiles, $u_{j,g}$, of Income Groups According to WB (2009) Classification, Base-year 2009

	Usage intensity in income group (Increase in usage intensity from lower group)				Income Group
Durable Good	Low	Low Middle	High Middle	High	with Largest Increase
air condition	0.054	0.075	0.154	0.311	
		(0.021)	(0.079)	(0.157)	high
camera	0.013	0.021	0.058	0.132	
		(0.008)	(0.036)	(0.074)	high
car	0.009	0.013	0.020	0.046	
		(0.004)	(0.007)	(0.026)	high
cellphone	0.283	0.372	0.508	0.642	
		(0.089)	(0.136)	(0.133)	high middle
computer	0.030	0.048	0.099	0.192	
		(0.019)	(0.051)	(0.092)	high
cycles	0.176	0.236	0.319	0.347	
		(0.060)	(0.083)	(0.028)	high middle
electric fan	0.390	0.487	0.580	0.646	
		(0.096)	(0.093)	(0.066)	low middle
fridge	0.124	0.148	0.255	0.336	
		(0.024)	(0.106)	(0.081)	high middle
homevideo appl.	0.316	0.364	0.463	0.561	
		(0.048)	(0.100)	(0.097)	high middle
kitchen appl.	0.338	0.423	0.618	0.832	
		(0.084)	(0.195)	(0.214)	high
motorcycle	0.076	0.111	0.117	0.107	
		(0.035)	(0.006)	(-0.009)	low middle
radio	0.039	0.056	0.112	0.161	
		(0.017)	(0.056)	(0.048)	high middle
satellite dish	0.029	0.035	0.029	0.040	
		(0.006)	(-0.006)	(0.011)	high
sewing machine	0.073	0.077	0.110	0.120	
		(0.004)	(0.033)	(0.010)	high middle
telephone	0.107	0.142	0.228	0.304	
		(0.035)	(0.086)	(0.076)	high middle
washing machine	0.159	0.180	0.258	0.336	
		(0.021)	(0.078)	(0.078)	high middle

Notes: All data are from CHNS, wave 2009. Households are grouped according to household income per capita in constant in constant 2009 Yuan: low income (2'149 Yuan), lower middle income (2'150 - 8'514 Yuan), upper middle income (8'515 - 16'499 Yuan), high income (16'500 or more). The first row of each durable good shows usage intensities (the $\bar{u}_{j,g} = u_{j,g,t=2009}$s), i.e. the average number of goods per capita, and the second row shows the increase in the usage intensity (in brackets) moving from the income group below into the income group of that column.

Table A.3: Correspondence between CHNS Durable Good Categories and ASIP Industries

Durable Good in CHNS	ndustry Name in CIC	CIC pre 2003	CIC post 2003	Industry in Analysis
air condition	Home air conditioner manufacturers	4065	3952	air condition
bicycle	Bicycle manufacturers	3740	3741	cycles
camera	Camera and equipment manufacturing	4254	4153	camera
car	Automobile manufactoring	3721-3725	3721	car
cellphone	Mobile communications and terminal equipment manufacturing	-	4014	cellphone
colour TV	Home video equipment manufacturing	4171	4071	homevideo appliances
computer	Computer machine manufacturing	4141	4041	computer
DVD	Home video equipment manufacturing	4171	4071	homevideo appliances
electric fan	Manufacturers of household electrical appliances ventilation	4064	3953	electric fan
refrigerator	Household refrigerating appliances manufacturing	4063	3951	refrigerator
microwave	Household kitchen appliances manufacturing	4066	3954	kitchen appliances
motorcycle	Motorcycle manufacturing	3731	3731	motorcycle
pressure cooker	Household kitchen appliances with manufacturing	4066	3954	kitchen appliances
radio	Home audio equipment manufacturing	4172	4072	radio
rice cooker	Household kitchen appliances manufacturing	4066	3954	kitchen appliances
satellite dish	Radio and television receiving equipment manufacturing	4130	4032	satellite dish
sewing machine	Sewing machinery manufacturing	3674	3653	sewing machine
telephone	Communication terminal equipment manufacturing	4113	4013	telephone
tricycle	Bicycle manufacturing	3740	3741	cycles
washing machine	Household cleaning electrical appliances manufacturing	4061, 4062	3955	washing machine

Table A.4: Summary Statistics

Variable	Mean	Std. dev.	Min.	Max.	# Observations
$\ln TFP_{i,j,t}$	5.245	1.150	1.440	10.643	30883
$\ln Laborproductivity_{i,j,t}$	4.025	1.141	-1.214	9.694	30883
$\ln MS^{actual}_{j,t,t+4}$	16.918	0.974	14.630	18.543	111
$\ln MS^{potential}_{j,t,t+4}$	16.879	0.927	14.869	18.274	123
$SIZE_{i,j,t}$	5.437	1.309	2.079	12.145	30883
$1(FOE_{i,j,t} = 1)$	0.375	0.484	0	1	30883
$1(SOE_{i,j,t} = 1)$	0.072	0.259	0	1	30883
$1(COE_{i,j,t} = 1)$	0.268	0.443	0	1	30883
$1(DPE_{i,j,t} = 1)$	0.281	0.449	0	1	30883
$1(AGE_{i,j,t} > \overline{AGE})$	0.535	0.498	0	1	30876
$1(COAST_{i,j,t} = 1)$	0.845	0.361	0	1	30883
$HHI_{j,t}$	568.085	459.197	99.2	2863.28	30883
$1(EXP_{i,j,t} > 0)$	0.491	0.499	0	1	30866
$TECHPOT_{j,t}$	2.618	0.521	1.111	4	155

Notes: $\ln TFP_{i,j,t}$ denotes log of total factor productivity of firm i in industry j and year t, estimated as described in Appendix 4.B.2. $\ln Laborproductivity_{i,j,t}$ is measured as the log of firm's value added over its number of employees. $SIZE_{i,j,t}$ the log of number of workers. $\ln MS^{actual}_{j,t,t+4}$ and $\ln MS^{potential}_{j,t,t+4}$ are actual and potential market size measured in log-terms, respectively and over a five year time horizon as described in the text. $1(FOE_{i,j,t} = 1)$, $1(SOE_{i,j,t} = 1)$, $1(COE_{i,j,t} = 1)$ and $1(DPE_{i,j,t} = 1)$ indicate whether a firm is foreign owned, state owned, collectively owned or a domestic private enterprise, respectively. $1(AGE_{i,j,t} > \overline{AGE})$ indicated whether a firm is above the median age of all firms in the sample. $1(COAST_{i,j,t} = 1)$ is a dummy for whether a firm is located in a coastal province. $HHI_{j,t}$ is the Hirschmann-Herfindahl index as described in the text. $1(EXP_{i,j,t} > 0)$ is a dummy for whether a firm has positive export sales and $TECHPOT_{j,t}$ is the world wide technology potential assessed by Swiss firms in the KOF Innovation Survey. Data is based on the 10% trimmed sample (see Section 4.2.2).

Table A.5: Summary Statistics at Industry Level (part I)

		$\ln TFP_{i,j,t}$		$\ln Investment_{i,j,t}$		$\ln Laborproductivity_{i,j,t}$		$\ln MS^{actual}_{j,t,t+4}$		$\ln MS^{potential}_{j,t,t+4}$		$SIZE_{i,j,t}$	
Industry	# Observations	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
air condition	1936	5.319	1.167	7.607	2.460	4.344	1.071	16.795	0.294	16.814	0.199	5.354	1.281
camera	851	5.246	1.120	7.529	2.515	3.848	1.122	15.789	0.045	15.891	0.241	5.714	1.282
car	3156	5.349	1.431	8.555	2.923	4.036	1.399	14.978	0.264	15.094	0.173	6.160	1.521
cellphone	1019	6.179	1.325	8.470	2.461	4.864	1.347	18.478	0.091	18.173	0.032	5.682	1.418
computer	1317	5.943	1.474	8.157	2.940	4.748	1.353	16.221	0.456	16.478	0.187	5.659	1.659
cycles	4052	4.839	0.825	6.519	2.030	3.748	0.878	17.213	0.178	17.505	0.063	5.035	1.025
electric fan	1504	4.999	0.943	7.091	2.168	3.843	0.938	18.157	0.046	18.147	0.047	5.299	1.199
fridge	1087	5.205	1.154	7.725	2.509	4.198	1.057	17.115	0.215	17.200	0.120	5.437	1.412
homevideo appl.	2397	5.708	1.302	7.691	2.477	4.094	1.255	18.151	0.069	18.008	0.066	5.836	1.358
kitchen appl.	2160	5.066	0.854	6.996	2.241	4.057	0.898	18.178	0.110	18.129	0.101	5.036	1.188
motorcycle	1974	5.481	1.106	7.730	2.323	4.316	1.063	16.828	0.056	16.746	0.011	5.430	1.193
radio	3191	5.126	0.967	6.682	2.394	3.576	0.993	15.966	0.470	16.510	0.145	5.580	1.209
satellite dish	1313	5.048	0.901	6.571	2.062	3.855	0.968			15.331	0.020	4.988	1.055
sewing machine	2026	4.828	0.827	6.867	2.034	3.788	0.902	16.145	0.286	16.422	0.072	4.999	0.938
telephone	1581	5.370	1.178	7.422	2.433	4.085	1.314	17.319	0.333	17.177	0.110	5.465	1.342
washing machine	1319	5.088	0.995	7.467	2.163	4.135	0.989	17.244	0.108	17.247	0.095	5.305	1.144
All industries	30883	5.244	1.150	7.352	2.475	4.025	1.141	16.918	0.974	16.879	0.927	5.437	1.309

Notes: $\ln TFP_{i,j,t}$ denotes log of total factor productivity of firm i in industry j and year t, estimated as described in Appendix 4.B.2. $\ln Investment_{i,j,t}$ is the yearly difference of a firm's fixed assets in logs. $\ln Laborproductivity_{i,j,t}$ is measured as the log of firm's value added over its number of employees. $SIZE_{i,j,t}$ is defined as the log of number of workers. $\ln MS^{actual}_{j,t,t+4}$ and $\ln MS^{potential}_{j,t,t+4}$ are actual and potential market size measured in logs, respectively, over a five year time horizon as described in the text. Data is based on the 10% trimmed sample (see Section 4.2.2).

Table A.6: Summary Statistics at Industry Level (part 2)

	$1(FOE_{i,j,t}=1)$		$1(SOE_{i,j,t}=1)$		$1(COE_{i,j,t}=1)$		$1(DPE_{i,j,t}=1)$		$1(AGE_{i,j,t}>\overline{AGE})$		$1(COAST_{i,j,t}=1)$		$HHI_{j,t}$	
Industry	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
air condition	0.396	0.489	0.024	0.152	0.320	0.467	0.259	0.438	0.553	0.497	0.847	0.360	955.92	304.01
camera	0.757	0.429	0.067	0.250	0.086	0.280	0.089	0.285	0.541	0.499	0.919	0.273	854.45	191.25
car	0.176	0.381	0.307	0.461	0.427	0.495	0.085	0.279	0.645	0.479	0.529	0.499	524.65	112.68
cellphone	0.608	0.488	0.024	0.152	0.166	0.372	0.200	0.400	0.421	0.494	0.831	0.375	1145.34	243.33
computer	0.501	0.500	0.092	0.289	0.260	0.439	0.146	0.353	0.450	0.498	0.764	0.425	643.06	305.23
cycles	0.380	0.485	0.030	0.172	0.234	0.424	0.354	0.478	0.580	0.494	0.954	0.209	144.98	41.24
electric fan	0.242	0.428	0.029	0.169	0.358	0.480	0.364	0.481	0.557	0.497	0.958	0.200	644.09	630.87
fridge	0.240	0.427	0.055	0.228	0.389	0.488	0.314	0.464	0.529	0.499	0.760	0.427	1564.42	621.97
homevideo appl.	0.527	0.499	0.064	0.245	0.226	0.418	0.181	0.385	0.477	0.500	0.873	0.333	428.43	220.59
kitchen appl.	0.299	0.458	0.004	0.064	0.207	0.406	0.489	0.500	0.443	0.497	0.977	0.149	922.35	407.41
motorcycle	0.130	0.336	0.082	0.275	0.367	0.482	0.419	0.494	0.456	0.498	0.710	0.454	376.56	43.65
radio	0.598	0.490	0.027	0.162	0.155	0.362	0.219	0.414	0.547	0.498	0.961	0.193	299.80	125.98
satellite dish	0.361	0.480	0.058	0.234	0.202	0.402	0.379	0.485	0.538	0.499	0.805	0.396	368.70	103.78
sewing machine	0.226	0.418	0.041	0.199	0.299	0.458	0.434	0.496	0.551	0.498	0.914	0.281	353.68	97.26
telephone	0.474	0.499	0.118	0.323	0.237	0.425	0.168	0.374	0.592	0.492	0.806	0.396	888.87	795.26
washing machine	0.318	0.466	0.025	0.156	0.293	0.455	0.363	0.481	0.528	0.499	0.903	0.296	541.85	165.44
All industries	0.375	0.484	0.072	0.259	0.269	0.443	0.282	0.450	0.536	0.499	0.846	0.361	568.09	459.20

Notes: $1(FOE_{i,j,t}=1)$, $1(SOE_{i,j,t}=1)$, $1(COE_{i,j,t}=1)$ and $1(DPE_{i,j,t}=1)$ indicate whether a firm is foreign owned, state owned, collectively owned or a domestic private enterprise, respectively. $1(AGE_{i,j,t}>\overline{AGE})$ indicated whether a firm is above the median age of all firms in the sample. $1(COAST_{i,j,t}=1)$ is a dummy for whether a firm is located in a coastal province. $HHI_{j,t}$ is the Hirschmann-Herfindahl index as described in the text. Data is based on the 10% trimmed sample (see Section 4.2.2).

Table A.7: Summary Statistics at Industry Level (part 3)

	$1(EXP_{i,j,t} > 0)$		$EXPSH_{i,j,t}$		$TECHPOT_{j,t}$	
Industry	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
air condition	0.380	0.486	0.149	0.292	2.566	0.353
camera	0.763	0.426	0.604	0.429	2.488	0.333
car	0.214	0.410	0.019	0.096	2.827	0.093
cellphone	0.517	0.500	0.280	0.381	2.368	0.127
computer	0.411	0.492	0.280	0.421	3.466	0.380
cycles	0.539	0.499	0.331	0.409	2.570	1.113
electric fan	0.493	0.500	0.352	0.430	2.566	0.353
fridge	0.392	0.488	0.134	0.269	2.566	0.353
homevideo appl.	0.605	0.489	0.412	0.433	2.440	0.115
kitchen appl.	0.529	0.499	0.359	0.427	2.566	0.353
motorcycle	0.391	0.488	0.134	0.258	2.570	1.113
radio	0.691	0.462	0.578	0.450	2.574	0.440
satellite dish	0.497	0.500	0.339	0.418	2.440	0.115
sewing machine	0.496	0.500	0.237	0.330	2.754	0.013
telephone	0.462	0.499	0.302	0.414	2.440	0.115
washing machine	0.559	0.497	0.271	0.370	2.566	0.353
All industries	0.491	0.500	0.297	0.404	2.618	0.522

Notes: $1(EXP_{i,j,t} > 0)$ is a dummy for whether a firm has positive export sales and $EXPSH_{i,j,t}$ is the share of export sales on total sales of a firm. $TECHPOT_{j,t}$ is the world wide technology potential assessed by Swiss firms in the KOF Innovation Survey. Data is based on the 10% trimmed sample (see Section 4.2.2).

Table A.8: Effect of Market Size on Log TFP including Controls

Dep. Variable	$\ln TFP_{i,j,t}$					
Mean	5.137	5.137	5.137	5.137	5.137	5.137
St.Dev.	1.161	1.161	1.161	1.161	1.161	1.161
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln MS^{actual}_{j,t,t+4}$	0.188	0.0628	0.0628	0.549	0.272	0.272
	[0.0813]**	[0.0525]	[0.0395]	[0.185]***	[0.132]**	[0.0828]***
Size		0.346	0.346		0.344	0.344
		[0.0135]***	[0.0112]***		[0.0133]***	[0.0113]***
Admin_FE		0.134	0.134		0.132	0.132
		[0.0277]***	[0.0270]***		[0.0274]***	[0.0270]***
Admin_SOE		-0.741	-0.741		-0.740	-0.740
		[0.0373]***	[0.0523]***		[0.0370]***	[0.0523]***
Admin_COE		0.0351	0.0351		0.0313	0.0313
		[0.0219]	[0.0256]		[0.0222]	[0.0257]
Age		-0.237	-0.237		-0.236	-0.236
		[0.0177]***	[0.0193]***		[0.0174]***	[0.0193]***
Region		0.0410	0.0410		0.0414	0.0414
		[0.0281]	[0.0366]		[0.0286]	[0.0366]
HHI		1.60e-05	1.60e-05		6.36e-06	6.36e-06
		[2.15e-05]	[2.30e-05]		[2.69e-05]	[2.33e-05]
Method	OLS	OLS	OLS	2SLS	2SLS	2SLS
Observations	20,167	20,160	20,160	20,167	20,160	20,160
R^2	0.111	0.278	0.278	0.106	0.277	0.277
Clustering	Ind. x Year	Ind. x Year	Firm	Ind. x Year	Ind. x Year	Firm
No of Clusters				111	111	7662
F-Stats				27.68	26.70	1480

Notes: ***, **, * denote significance on the 1%, 5% and 10% level, respectively. Observations below the 10 percentile of value added each year are excluded. All columns include year and industry fixed effects. $\ln MS^{actual}_{j,t,t+4}$ is instrumented with $\ln MS^{potential}_{j,t,t+4}$.

Table A.9: Robustness Analysis: Controlling for Exports and Technology Supply Shocks

Dep. Variable	$\ln TFP_{i,j,t}$					
Mean	5.137	5.138	4.957	5.355	5.137	5.138
St. Dev.	1.161	1.160	1.102	1.191	1.161	1.160
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln MS^{actual}_{j,t,t+4}$	0.272	0.274	0.408	-0.164	0.265	0.267
	[0.132]**	[0.133]**	[0.141]***	[0.169]	[0.135]**	[0.136]**
$1(EXP_{i,j,t} > 0)$		0.0539				0.0540
		[0.0274]**				[0.0274]**
$TECHPOT_{j,t}$					-0.00541	-0.00558
					[0.0236]	[0.0240]
Sample	All	All	Non-Exporters	Exporters	All	All
Method	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Observations	20,160	20,147	10,980	9,167	20,160	20,147
R^2	0.277	0.277	0.206	0.368	0.277	0.277
F-Stats	26.70	26.88	42.25	15.87	21.17	21.31

Notes: ***, **, * denote significance on the 1%, 5% and 10% level, respectively. Robust standard errors (clustered on the industry-year level jt) are given in parentheses. Observations below the 10 percentile of value added each year are excluded. All columns include year and industry fixed effects as well as a set of firm- and industry-level controls (the log of number of workers, age (measured by a dummy), a dummy for collective, state and foreign ownership, coastal location, respectively and the Hirschmann-Herfindahl index). $1(EXP_{i,j,t} > 0)$ is one if a firm has positive export sales. $\ln MS^{actual}_{j,t,t+4}$ is instrumented with $\ln MS^{potential}_{j,t,t+4}$. $TECHPOT_{j,t}$ is the world wide technology potential assessed by Swiss firms in the KOF Innovation Survey.

Table A.10: First Stage Regression including Controls

Dep. Variable	$\ln MS^{actual}_{j,t,t+4}$		
	(1)	(2)	(3)
$\ln MS^{potential}_{j,t,t+4}$	1.967	1.955	1.955
	[0.374]***	[0.378]***	[0.0508]***
Size		0.00529	0.00529
		[0.00136]***	[0.00135]***
Admin_FE		-0.00228	-0.00228
		[0.00414]	[0.00431]
Admin_SOE		-0.00329	-0.00329
		[0.00607]	[0.00775]
Admin_COE		-0.00435	-0.00435
		[0.00576]	[0.00435]
Age		-0.00276	-0.00276
		[0.00572]	[0.00364]
Region		-0.000619	-0.000619
		[0.00432]	[0.00458]
HHI		1.75e-05	1.75e-05
		[6.05e-05]	[6.47e-06]***
Observations	20,167	20,160	20,160
R^2	0.968	0.968	0.968
Clustering	Ind. x Year	Ind. x Year	Firm
No of Clusters	111	111	7662
F-Stats	27.68	26.70	1480

Notes: ***, **, * denote significance on the 1%, 5% and 10% level, respectively. Observations below the 10 percentile of value added each year are excluded. All columns include year and industry fixed effects. The reported R^2 reported equals the partial R^2.

Table A.11: First Stage Regression - Trimming

Dep. Variable	$\ln MS^{actual}_{j,t,t+4}$				
	(1)	(2)	(3)	(4)	(5)
$\ln MS^{potential}_{j,t,t+4}$	1.990	1.970	1.955	1.951	1.907
	[0.381]***	[0.380]***	[0.378]***	[0.374]***	[0.358]***
Observations	22,328	21,241	20,160	16,900	11,412
R^2	0.244	0.241	0.239	0.241	0.247
Trimming	10%	0%	5%	25%	50%
No of Clusters	111	111	111	111	111
F-Stats	27.32	26.95	26.70	27.27	28.41

Notes: ***, **, * denote significance on the 1%, 5% and 10% level, respectively. Robust standard errors (clustred on the industry-year level jt) are given in parentheses. All columns include year and industry fixed effects as well as a set of firm- and industry-level controls (the log of number of workers, age (measured by a dummy), a dummy for collective, state and foreign ownership, coastal location, respectively and the Hirschmann-Herfindahl index). The reported R^2 reported equals the partial R^2.

Table A.12: Robustness Analysis: First Stage Regression

Dep. Variable	$\ln MS^{actual}_{j,t,t+4}$ $\ln MS^{actual}_{j,t,t+4} \times 1(EXP_{i,j,t} > 0)$				
	(1)	(2)	(3)	(4)	(5)
$\ln MS^{potential}_{j,t,t+4}$	1.955	1.957	1.956	1.951	1.954
	[0.378]***	[0.378]***	[0.375]***	[0.424]***	[0.423]***
$\ln MS^{potential}_{j,t,t+4} \times 1(EXP_{i,j,t} > 0)$			-0.0217		
			[0.00584]***		
$1(EXP_{i,j,t} > 0)$	No	Yes	Yes	No	Yes
$TECHPOT_{j,t}$	No	No	No	Yes	Yes
Observations	20,160	20,147	20,147	20,160	20,147
R^2	0.239	0.240	0.248	0.223	0.223
R^2_2			0.885		
F-Stats	26.70	26.88		21.17	21.31
F-Stats1			40.31		
F-Stats2			839.5		

Notes: ***, **, * denote significance on the 1%, 5% and 10% level, respectively. Robust standard errors (clustered on the industry-year level jt) are given in parentheses. Observations below the 10 percentile of value added each year are excluded. All columns include year and industry fixed effects as well as a set of firm- and industry-level controls (the log of number of workers, age (measured by a dummy), a dummy for collective, state and foreign ownership, coastal location, respectively and the Hirschmann-Herfindahl index). The reported R^2 reported equals the partial R^2. In Column (3) F-Stats1 and the R^2 are on the first stage of $\ln MS^{potential}_{j,t,t+4}$, and F-Stats2 and R^2_2 are w.r.t. $\ln MS^{potential}_{j,t,t+4} \times 1(EXP_{i,j,t} > 0)$.

Table A.13: Robustness Analysis: First Stage Regression

Dep. Variable	$\ln MS^{actual}_{j,t,t+4}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln MS^{potential}_{j,t,t+4}$	1.955	1.957	1.559	2.258	1.951	1.954
	[0.378]***	[0.378]***	[0.391]***	[0.347]***	[0.424]***	[0.423]***
$1(EXP_{i,j,t} > 0)$	No	Yes	-	-	No	Yes
$TECHPOT_{j,t}$	No	No	No	No	Yes	Yes
Sample	All	All	Exporters	Non-Exporters	All	All
Observations	20,160	20,147	9,167	10,980	20,160	20,147
R^2	0.239	0.240	0.152	0.335	0.223	0.223
F-Stats	26.70	26.88	15.87	42.25	21.17	21.31

Notes: ***, **, * denote significance on the 1%, 5% and 10% level, respectively. Robust standard errors (clustered on the industry-year level jt) are given in parentheses. Observations below the 10 percentile of value added each year are excluded. All columns include year and industry fixed effects as well as a set of firm- and industry-level controls (the log of number of workers, age (measured by a dummy), a dummy for collective, state and foreign ownership, coastal location, respectively and the Hirschmann-Herfindahl index). The reported R^2 reported equals the partial R^2.

Table A.14: First Stage Regression - Sample Log Laborproductivity

Dep. Variable	$\ln MS^{actual}_{j,t,t+4}$		
	(1)	(2)	(3)
$\ln MS^{potential}_{j,t,t+4}$	1.955	1.955	1.954
	[0.378]***	[0.0508]***	[0.423]***
Observations	20,160	20,160	20,147
R^2	0.239	0.239	0.223
Clustering	Industry x Year	Firm	Industry x Year
No of Clusters	111	7662	111
F-Stats	26.70	1480	21.31

Notes: ***, **, * denote significance on the 1%, 5% and 10% level, respectively. Observations below the 10 percentile of value added each year are excluded. All columns include year and industry fixed effects and a set of firm- and industry-level controls (the log of number of workers, age (measured by a dummy), a dummy for collective, state and foreign ownership, coastal location, respectively and the Hirschmann-Herfindahl index). Column (4) in addition introduces a dummy for positive exports, $1(EXP_{i,j,t} > 0)$ and the supply side control, $TECHPOT_{j,t}$. The reported R^2 reported equals the partial R^2.

Table A.15: First Stage Regression on the Industry Level

Dep. Variable	$\ln MS^{actual}_{j,t,t+4}$	
	(1)	(2)
$\ln MS^{potential}_{j,t,t+4}$	1.224	1.590
	[0.448]***	[0.407]***
$1(EXP_{i,j,t} > 0)$	No	Yes
$TECHPOT_{j,t}$	No	Yes
Observations	111	111
R^2	0.08	0.12
Observations	111	111
F-Stats	7.459	15.25

Notes: ***, **, * denote significance on the 1%, 5% and 10% level, respectively. Robust standard errors are given in parentheses. Observations below the 10 percentile of value added each year are excluded. All columns include year and industry fixed effects as well as the industry mean of the set of firm- and industry-level controls (the log of number of workers, age (measured by a dummy), a dummy for collective, state and foreign ownership, coastal location, respectively and the Hirschmann-Herfindahl index). Regressions are weighted by the number of firms within a sector. The reported R^2 reported equals the partial R^2.

4.B Data Appendix

4.B.1 Market Size & CHNS

Definition of Income Groups

Household income and household income per capita is provided by the CHNS in longitudinal data-files including the latest wave 2009.[42] Household disposable income in the CHNS is conceptualised as the sum of all sources of market and non-market incomes or revenues minus expenses on the household or individual level. We use household income deflated to constant 2009 Yuan, using the price deflator provided by the CHNS which is based on a standard NBS consumer basket allowing for price differences between urban and rural areas.
We split the income distribution into $g = 1, ..., G$ groups setting fixed income thresholds in constant 2009 Yuan and calculate the population share $i_{g,t}$ of each income group g for each survey year t.

In our baseline, we take inspiration from the World Bank's (World Bank, 2009) classification of countries[43] and divide households into four ($G = 4$) income groups: low income, lower middle income, upper middle income and high income. To account for sampling artefacts in the 2006 survey, we project household incomes per capita between 1997 and 2009 using the growth rate of average household income per capita in this period. The World Bank's thresholds in constant 2009 dollars and were converted into constant 2009 yuan. All dollar figures where converted into constant 2009 Yuan using the exchange rate and PPP adjustment factors.[44] To account for the small number of observations in early waves in some higher income groups, we slightly adjusted these thresholds with the largest adjustment for the threshold of the high income group.[45]

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[42]See Beerli (2010) for a more detailed description.

[43]The World Bank (2009) classifies economies according to their 2009 GNI per capita, calculated using the World Bank Atlas method. The following thresholds are set: low income, US $ 995 or less; lower middle income, US $ 996 - US $ 3'945; upper middle income, US $ 3'946 - US $ 12'196; and high income, US $ 12'196 or more.

[44]Dollar values are converted to constant 2009 using the China Version 2 exchange rate and PPP adjustment factor from the Penn World Tables 7.0, i.e. $threshold \times \frac{XRAT}{PPP}$. With some adjustments to account for small sampling of high income groups, this yields the following thresholds in constant 2009 Yuan: low income (2'149 Yuan), lower middle income (2'150 - 8'514 Yuan), upper middle income (8'515 - 16'499 Yuan), high income (16'500 or more).

[45]The adjusted thresholds are: low income, US $ 1'052, low middle income, US $ 1'053 -US $US 4'167, high middle income, US $ 4'168 - US $ 8'075, high income, US $ 8'076 or more.

Usage Profiles and Base-Year

The choice of a base-year for ownership profiles implies different assumptions about entrepreneurs expectations, on the one hand, and accuracy considerations on the other hand. Taking ownership profiles from a survey year at the beginning of our panel, e.g 1997, we assume that entrepreneurs base their expectations about ownership profiles on durable good prices and qualities from 1997. As Beerli (2010) shows in his analysis of durable good ownership between 1989 and 2006, depending on the durable good, ownership rates were generally increasing across the income distribution mainly explained by a substantial fall in durable goods prices but also by improvements in public service provision and other factors. Additionally, ownership rates increased unevenly across the income distribution with poor households gaining much more from price changes compared to richer income groups. This implies that the aggregate, potential ownership stocks based on the year 1997 will underestimate the true market size substantially. With respect to accuracy, picking 1997 as a base-year involves the problem that there are relatively few rich households (i.e. less than 1%) which makes the information about their ownership profiles relatively inaccurate.[46] Taking the latest survey year available, i.e. 2009, on the other hand, assumes that entrepreneurs form their expectations (about the future development of durable good sales) based on durable good prices and qualities from 2009. Since ownership rates generally increased over time, our potential ownership stock measure based on the year 2009 overestimates the true market size. Yet, since there are many more rich households in 2009 than in earlier years, their ownership profile should be estimated more accurately. Thus, independently from the choice of the base-year, potential stocks will be either over- or underestimated. Moreover, it means that potential sales, the difference between two years, will generally be lower than actual sales.[47]

Population Measure Implications

In the CHNS we observe a household's ownership and change in ownership status of a specific durable good variety j and without having information on its price and quality. Dealing with such a population measure of market size has some implications.[48] First, we can not distinguish between a car acquisition of one household to another household on

[46]Another problem is that some durable goods become available only in later survey years, e.g. cellphones from 2004.

[47]This is in line with the findings of Beerli (2010) who finds that the share of changes in aggregate ownership explained by income can differ substantially between different durable goods, being only 31% for color TVs.

[48]Note that Acemoglu and Linn (2004) use a similar population measure of drugs used in a certain age group.

a quality or price dimension. [49] All acquisition within the same durable good variety j receive the same (population) weight.[50] Thus, we think of the new car acquisition, which we observe in the CHNS, as an average car bought or a count measure of sales whose magnitude can only be compared across durable goods. Second and related, we can not distinguish between sales values of similar magnitude between different durable goods. A 1 percentage point sale of cars and a 1 percentage point sale of bicycles affects their respective industries with a similar magnitude although an average car differs from an average bicycle to a large extent in value terms.

4.B.2 Construction of Total Factor Productivity at the Firm-level

To construct a measure of firm-level productivity we follow an estimation procedure suggested by Levinsohn and Petrin (2003). They propose taking intermediate inputs as a proxy for unobserved shocks affecting a firm's input choice instead of investment as suggested by Olley and Pakes (1996). One advantage of this approach is strictly data driven as investment is zero for many firms in our dataset whereas intermediate inputs are not. As Levinsohn and Petrin (2003) show, taking investment as proxy for unobserved productivity shocks is only valid for firms reporting non-zero investment. We use the STATA implementation `levpet` to estimate the parameters of the production function:

$$y_{i,t} = \beta_0 + \beta_l l_{i,t} + \beta_k k_{i,t} + \beta_m m_{i,t} + \omega_{i,t} + \eta_{i,t}$$

using the logarithm of real intermediate inputs, $m_{i,t}$, as proxy variable. $y_{i,t}$ denotes the logarithm of real value added of firm i in year t, $l_{i,t}$ denotes the logarithm of the number of workers, $k_{i,t}$ the logarithm of the real capital stock, $\omega_{i,t}$ represents the unobserved productivity component and $\eta_{i,t}$ is an error term that is uncorrelated with input choices. The real capital stock variable was constructed following a procedure suggested by Brandt et al. (2012). Nominal values of value added and the capital stock measure were deflated using the input- and output-deflators provided by Brandt et al. (2012).

The estimation yields $\hat{\beta}_l = 0.176$ and $\hat{\beta}_k = 0.36$. According to Levinsohn and Petrin (2003), estimated productivity for firm i at time t is then given by

$$\hat{\omega}_{i,t} = \exp\left(y_{i,t} - \hat{\beta}_l l_{i,t} - \hat{\beta}_k k_{i,t}\right).$$

[49] This also includes second hand markets.

[50] Note that also acquisitions across time cannot be distinguished, although a car bought in 1989 and one bought in 2009 might, technically speaking, be a very different durable good.

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